Engineering Students' Engagement and Learning Outcomes: A Typological Approach

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Abstract

This research paper demonstrates our use of a typological approach to analyzing student engagement data. The typological approach aims to identify a range of student types based on the data measuring selected experiences, thus potentially uncovering inequality issues in student engagement research. In this study, we used two sets of institutional data that were collected in spring 2017 and 2020 from first and senior engineering students of a comprehensive Canadian university, by linking the National Survey of Student Engagement data to academic and co-curricular information. Our analysis identified four student types: highly engaged, moderately engaged, externally engaged, and disengaged. This typology was more associated with two self-reported learning outcomes (perceived gains in professional skills and perceived gains in technical skills) than objective learning outcomes (retention in the second year, graduation within five years, and academic performance measured by CGPA). One distinctive student type was the Externally Engaged learners, who constituted a small proportion but deserve attention as they were more likely to have marginalized life situations than students in other types. In light of the framework of constructive typology, our analyses offer insights on three inter-related themes: engagement-based student typology, equity and diversity in a student typology, and student typology as a constructed type.

Key words: student engagement, learning outcomes, constructive typology

1. Introduction

Student engagement is an important concept in research on postsecondary student experience. *Student engagement* means "the quality of effort students themselves devote to educationally purposeful activities that contribute directly to desired outcomes" [1] (p. 555). Within the engineering education communities, student engagement is a presumably desired goal to achieve in engineering courses and other academic activities. This is evident in the papers published in the proceedings of the American Society for Engineering Education annual conferences. Our search in the PEER repository in January 2024 showed that most of the papers with a focus on student engagement (139 in total) that were published between 2003 to 2023 reported how various educational interventions, such as use of distinctive pedagogies (e.g., project-based learning [2]; service learning [3]; game-based learning [4]), could enhance student engagement. While these studies contribute to identifying effective pedagogical approaches to enhancing the engagement of students at large, they were not designed to investigate who were more, or less, engaged in the educational practice; therefore, they do not inform how those students who were less engaged in learning could be better supported to achieve optimal learning outcomes.

In this paper, we explore the use of a typological approach to analyzing student engagement data. The typological approach aims to identify a range of student types based on data measuring selected experiences; these student types include those who are low on the spectrum of the measurements as well as those who do well. As such, the typological approach helps to uncover inequality issues in student engagement research by being better able to identify at-risk students than the correlational design that is widely used in student engagement research. In addition, the typological approach allows researchers to examine inherently integrated student experiences in a holistic manner, rather than disaggregating them. The approach has wide applications in engineering education research and practice. It could be used to examine the learning experiences of engineering students in an engineering school, and in a particular course that involved an instructional innovation. The approach will allow educators to identify which student groups may be disadvantaged or marginalized in a particular learning environment—likely less represented students in engineering programs—so that actions can be taken to better support these students.

To illustrate the typological approach, in this paper we used the National Survey of Student Engagement (NSSE) survey data collected from engineering students in two years (2017 and 2020) in a Canadian comprehensive university. We attempted to address the following research questions:

1. In what ways might engineering students be categorized based on their academic, social, co-curricular and extra-curricular experiences?
2. How do these categories relate to students' learning outcomes? Do students in these categories differ in their socio-demographical background?
3. Do students shift between these engagement-based categories from the first year to the final year? In other words, how does students' level of engagement change from the first year to the final year?

By addressing these questions, this paper will, on one hand, contribute to raising awareness among engineering educators of the typological approach to student data, and, on the other hand, enhance the scholarship on student engagement and learning outcomes in engineering education research.

2. Literature Review

2.1 Student Engagement in Higher Education Research

In higher education research, student engagement is recognized as "a family of constructs that measure the time and energy students devote to educationally purposeful activities—activities that matter to learning and student success [5, 6]. These constructs include "quality of effort" [7, 8], student involvement [9, 10], and student integration [11-13]. Student engagement involves multiple dimensions: behavioral, emotional, cognitive, social, financial and technological [14, 15]. As student engagement has been defined based on multiple perspectives, theoretical traditions, and educational contexts (Kahu, 2011), there may not be a consensus about the definition and measurement of student engagement [15, 16]. While some maintain that "[s]tudents always lie at the heart of conversations about student engagement" (p. 3) [17], others believe that it is important to recognize the role of postsecondary institutions in student engagement [18-20]. Consequently, it is posited that student engagement consists of two components: (a) the extent to which students participate in educationally effective activities; and (b) the institutional resources, learning opportunities and services, and students' perceptions of the institutional environment that supports student learning and development [18-20].

Research on student engagement has been rooted in a well-established field of inquiry on how postsecondary students' experiences affect their learning and development [21-24]. The general conclusion of this body of literature is correlational, that is, the greater the students' engagement in curricular and co-curricular activities on campus, the greater their level of cognitive and psychosocial development. For this reason, student engagement has been well recognized as a predictor of student learning and an important factor of student success [5, 25, 26]. The positive correlation between student engagement and learning outcomes has been reported extensively in higher education literature. For example, a study that used multi-institutional data collected from the National Survey of Student Engagement (NSSE) [27] reported that all student engagement constructs were positively associated with various self-reported learning outcomes.

While most student engagement related research has adopted a correlational research design, a much smaller set of studies has used a typological approach [18, 28-30]. In particular, two studies used NSSE student engagement indicators for analysis and identified these student typologies: high-interaction students, traditional-learning-focused students, and disengaged students [31] and; academics, conventionals, unconventionals, and disengaged [32]. As shown in these examples, rather than examining the association between student engagement and desired outcomes, use of the typological approach generated a full range of student types and revealed the characteristics of those students who were less engaged. As such, the typological approach contributes to equity research. Another advantage is that the typological approach takes stock of student experiences holistically, instead of dissecting them, as observed in a typology study in engineering education [29]. Taking NSSE data for example, one can observe that the typological approach allows a study to encompass students' academic, social and co-/extra-curricular experiences on and off campus into the analysis.

2.2 Student Engagement in Engineering Education Research

Along with the development of higher education research on student engagement, research on engineering students' engagement appears to have emerged in the early 2000s, as suggested by an article on assessment in engineering education [33]. A couple of major projects seem to have facilitated this movement within engineering education communities. One was the development of the Academic Pathways of People Learning Engineering Survey (APPLES) instrument [34] as part of the Academic Pathways Study undertaken by the Center for the Advancement of Engineering Education at the University of Washington. Another was the study "Measuring Student and Faculty Engagement in Engineering Education" [35] undertaken by the Center for the Advancement of Scholarship on Engineering Education of the National Academy of Engineering. A third one was the "Engineering Change: A Study of the Impact of EC2000" project at the Centre for the Study of Higher Education, the Pennsylvania State University [36]. In 2008, a *Journal of Engineering Education* paper [37] was published to capture these initiatives that all addressed student engagement in some ways. This paper highlighted the role of faculty engagement to student engagement, and tried to stimulate more interest in student and faculty engagement in engineering. Similarly, a doctoral thesis reported that among the five factors included in the study, faculty provided the most significant influence on undergraduate engineering students and their learning outcomes [15].

The following four research areas can be identified in engineering education research on student engagement.

- The definition and conceptualization of student engagement. For example, a study that focused on first- and second-year engineering students found that student engagement was exhibited in students' class participation, research participation, and interactions with their peers and professors, and concluded that there would not be one single definition of engagement for engineering students [38].
- Investigation into the correlates of student engagement. For instance, a study conducted in a Canadian engineering school found that supports in the learning environment were one of the best predictors for engineering students' engagement with two problem-based learning curricula [39]. One important finding in this research area is that the levels of engineering students' engagement varied by sociodemographic characteristics such as gender and race. Men and women engineering students are engaged in different types of out-of-class activities: women were more likely to participate in Living-Learning Communities and Music and Dance whereas men were more likely to engage in Job or Sports as their top activity [40].
- Instrument development to assess student engagement. One example was the Postsecondary Student Engagement Survey, which was created to measure undergraduate engineering students' engagement with co-curricular and extracurricular activities [41].
- Examining how instructional innovations or educational interventions could enhance student engagement. This research area involves intervention studies that include student engagement as an outcome. It constituted the largest research area within the ASEE conference papers that included "student engagement" in their titles, as revealed in our literature search on the PEER repository in January 2024. As an example, one study reported the contribution of a hands-on design experience to first-year engineering students' increased engagement with engineering studies [2]. This research area can overlap with the second one that examines the correlates of student engagement in studies on educational interventions (e.g., [39]). Studies in this research area do not often explicitly define the measurement of student engagement, which suggests that student engagement has been widely accepted within engineering education communities as a desired objective of student learning, even when it is not well defined or assessed.

3. Theoretical and Analytical Framework: Constructive Typology

The term "constructive typology," as a sociological term, perhaps first appeared in an article written by the American sociologist Howard Becker in 1940, which was published in the *American Sociological Review* [42]. In this early work about constructive typology, it was argued that sociologists construct types as a tool to explain social phenomena; these constructed types do not correspond exactly to actual empirical instance but may have a predictive power.

Later, in his work on typologies, John McKinney [43, 44] made the following assertions, which informed the present study.

- Typification—"perceiving the world and structuring it by means of types and typologies" ([44], p. 2) is a way of knowing as it involves knowledge reduction and generalization.
- Two orders of "types" are differentiated: (1) "the existential type," which represents the first order construct and is constructed by the participants in a social system; and (2) "the constructed type," which represents the "second order construct" and is created by researchers [44].
- The constructed type is "a construct made up of abstracted elements and formed into a unified conceptual pattern wherein there may be an intensification of one or more aspects of concrete experience" ([43], p. 12). It is "a purposive, planned selection, abstraction, combination, and (sometimes) accentuation of a set of criteria with empirical references that serves as a basis for comparison of empirical cases" ([43], p. 16). The words "selection," "intensification," and "accentuation" suggest that the type is constructed on the basis of selected features; and the word "abstraction" means that the constructed type represents a deviation from concrete experience.
- Regarding its function, the constructed type is a heuristic device developed by the research and used instrumentally for research purposes as it is "a devised system of attributes (criteria, traits, elements, aspects, etc.) not experienced directly in this form but *useful* as a *basis* for comparing and understanding the empirical world. [italics in the original text]" ([43], p. 12).
- The typological procedures can be "an aspect of pragmatic research methodology" ([44], p. 69).

Along a similar line, in 1994 Kenneth Bailey introduced the term "typology," which is another term for a classification (that is, "the general process of grouping entitles by similarity" [45]). He also posited that "a typology is generally multidimensional and conceptual." In addition, he introduced several methods for identifying typologies, including cluster analysis that was used in this paper.

4. Methodology

4.1 Data Sources

In this study, we used two sets of institutional data that were collected in spring 2017 and 2020 from first and senior engineering students at a comprehensive Canadian university. After data cleaning, the sample consisted of four data sets: 341 first-year students and 310 senior students in 2017; and 371 first-year students and 231 senior students in 2020, which constituted 21% to 30% of the students in the corresponding enrolled cohorts of the engineering school. Please note that the collection of the 2020 survey data was completed just before the breakout of the COVID-19 pandemic in March 2020 in North America; thus the data reflected the student experiences prior to the pandemic.

The bulk of these data sets were from the National Student Engagement Survey (NSSE) data that the university collected on a three-year basis (that is, 2017 and 2020 data). We included the following variables from the NSSE data into our study: 10 engagement indicators that fall under four themes (i.e., academic challenge, learning with peers, experience with faculty, and campus environment),[1] six variables that indicated students' experiences with co-curricular and extra-curricular activities, one variable indicating students' engagement with high-impact practices, and ten variables on perceived gains in certain skills. Based on the results from exploratory factor analysis, we grouped the ten variables on perceived gains into two categories: Perceived Gains in Professional Skills, and Perceived Gains in Technical Skills (Cronbach's alpha values= .84 and .80 respectively, for senior student data in 2020); and we created composite scores by averaging the existing responses to the relevant variables.

These NSSE data were linked with the following institutional data by the university's institutional research and data governance office and de-identified before being provided to the research team for analysis.

- Count of Co-curricular Record activities. The university has an established system to record students' participation in certain co-curricular activities when these activities are reported. It should be noted that not all the co-curricular activities that an individual student undertook have been captured in these records, due to failure to report on the part of the student or the faculty supervisor.
- Retention status in Year 2 (for first-year students).
- Graduation status (for senior students): whether a student has graduated within five years.
- Academic performance, which was measured by cumulative GPA by the time of the NSSE administration.

The research protocol of using these institutional data received the approval of the university's research ethics board.

4.2 Data Analysis Methods

For the purposes of the analysis, the variables in the linked data files were grouped into three categories: (1) student experience; (2) learning outcomes; (3) demographics and background. The details about the variables are included in Appendix A. The missing values in the original data sets for those variables constituted a very small proportion, with 7% as the highest. Before the data analysis, we imputed variables in the categories of student experiences and learning outcomes using the median values; and we did not apply any imputation to variables in the categories of demographics and background.

To address Research Question #1 (In what ways might engineering students be categorized based on their academic, social, co-curricular and extra-curricular experiences?), we performed:

- k-means cluster analysis on student experience variables *alone* to identify distinctive student clusters (using the "elbow method" to determine the optimal number of clusters);
- Welch's ANOVA test, followed by Games-Howell post-hoc test to inspect and characterize the differences across the identified clusters when the assumptions of normal

[1] How these engagement indicators were developed and their psychometric properties can be found at https://nsse.indiana.edu/nsse/survey-instruments/engagement-indicators.html

distribution and homogeneity of variances were violated. Based on the characteristics that differed significantly from other clusters, we named each cluster.

To address Research Question #2 (How do these categories relate to students' learning outcomes? Do students in these categories differ in their socio-demographical background?), we performed:

- regression analysis of the effects of identified clusters on learning outcomes—(a) perceived gains in technical skills, (b) perceived gains in professional skills, (c) CGPA, and (d) retention in the second year (for first-year students) or graduation status (for senior students). Linear regression analysis was applied to the first three outcomes; and binary logistic regression was applied to the fourth one.
- chi-square tests to examine how the student background characteristics were associated with each of the identified clusters.

To address Research Question #3 (Do students shift between these engagement-based categories from the first year to the final year? How does students' level of engagement change from the first year to the final year?), we implemented the following procedure:

- We first identified any shift in the engagement-based clusters from the first year to the final year of individual students by linking the 2017 first-year data and 2020 senior student data of the *same* students;
- When this cohort of the same students was too small, we examined the differences between the first year and the final year in all student experience variables for the clusters of the same type.

5. Results

In this section, we have presented the results from our analyses in three sub-sections to address each of the three research questions.

5.1 Four Student Clusters

Four distinctive clusters were identified through k-means cluster analysis of each of the four data sets. Table 1 shows the distribution of the four clusters in each data set.

Table 1. Four clusters identified via k-means cluster analysis

Year	Student cohorts	n	Highly Engaged	Moderately Engaged	Externally Engaged	Disengaged
2017	First-year	341	17%	39%	6%	38%
	Senior	310	20%	37%	7%	35%
2020	First-year	371	19%	34%	6%	41%
	Senior	231	33%	31%	5%	31%

A chi-square test of independence was performed on the cluster frequency distributions presented in the table in the years of 2017 and 2020 respectively; and the results showed no significant association between cohorts and the four clusters in both years of data at the .05

level, X^2 (3, N = 651) = .49, p = .92 in 2017, and X^2 (3, N = 602) = 5.39, p = .15 in 2020. Therefore, we observed from three of the four data sets (except the 2020 senior student data) that in each student cohort approximately one fifth were highly engaged learners, slightly over one third were moderately engaged learners, slightly over one third were relatively disengaged learners, and 6-7% were externally engaged learners.

Figures 1 to 4[2] visualize the differences across the four clusters in each student cohort (see the numerical values in Appendix B). The characteristics of these four clusters can be summarized as follows:

- Highly Engaged learners: They had the highest levels of engagement, among the four clusters, in most of the variables included for analysis—academic challenge, experiences with faculty, and campus environment. They were also actively engaged in volunteer and co-curricular activities but not the most engaged in these activities among the four clusters. In addition, they perceived the highest levels of gains in technical and professional skills from studying in the engineering school of the university.
- Moderately Engaged learners: Their levels of engagement in almost all the variables were about the average. Their level of engagement in learning from peers was about the same as the Highly Engaged learners.
- Externally Engaged learners: What makes this group distinctive from others was their highest levels of engagement, among the four clusters, in paid and volunteer work, participation in co-curricular activities, family care and commuting.
- Disengaged learners: They had the lowest levels of engagement, among the four clusters, in almost all variables, including academic and co-curricular activities. Their perceived gains in technical and professional skills were also the lowest.

[2] It should be noted that although three learning outcome variables (Perceived Gains in Professional Skills, Perceived Gains in Technical Skills, and CGPA) are included these graphs to visualize the differences across the clusters, these variables were not included in the k-means cluster analysis.

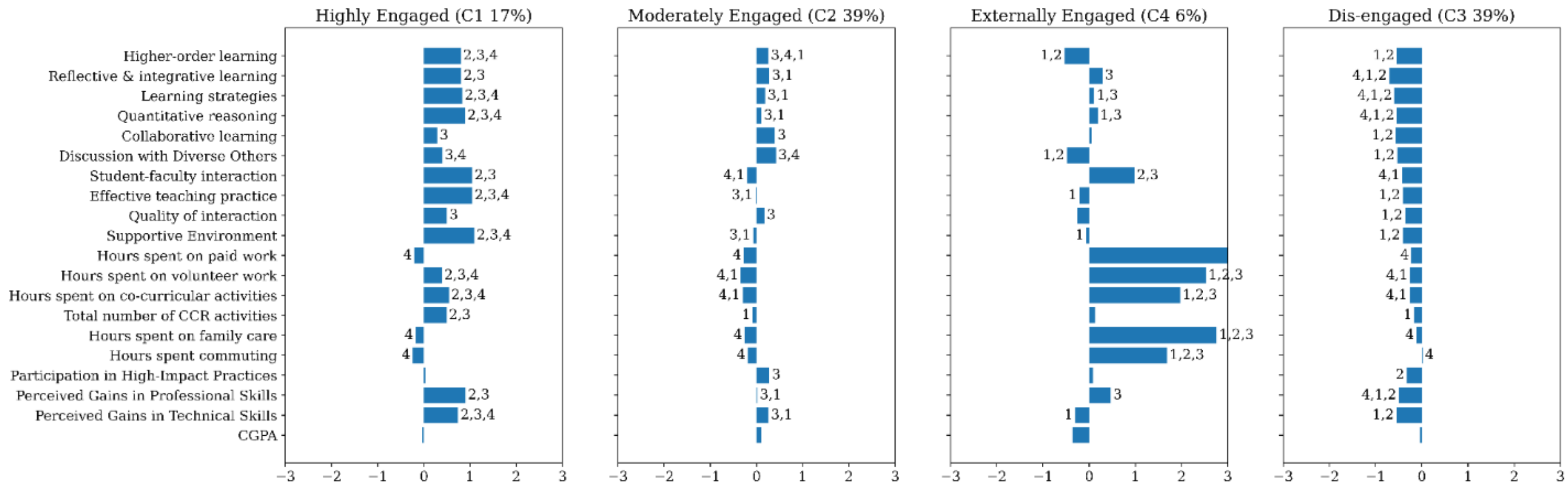

Figure 1. Averaged z-scores for the four clusters identified from the 2017 first-year student data.

Note: Numbers next to the bars represent those clusters that are significantly different on the specific variables. For example, Highly Engaged learners' higher-order learning is significantly different from C2 (Moderately Engaged learners), C3 (Dis-engaged learners), and C4 (Externally Engaged learners).

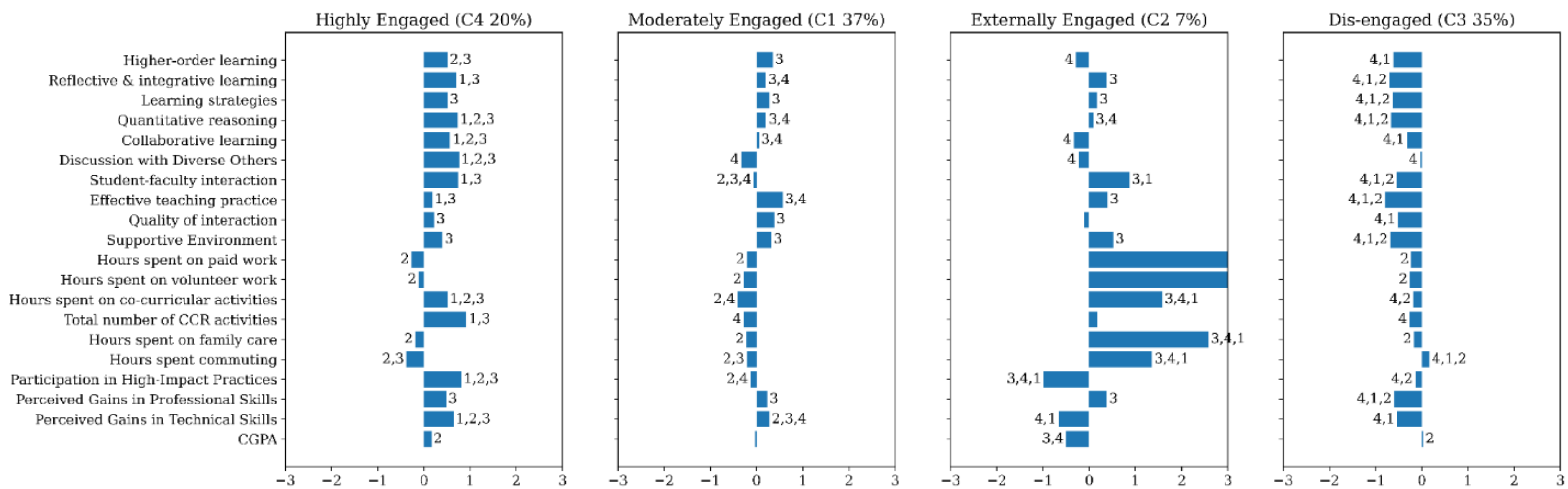

Figure 2. Averaged z-scores for the four clusters identified from the 2017 senior student data

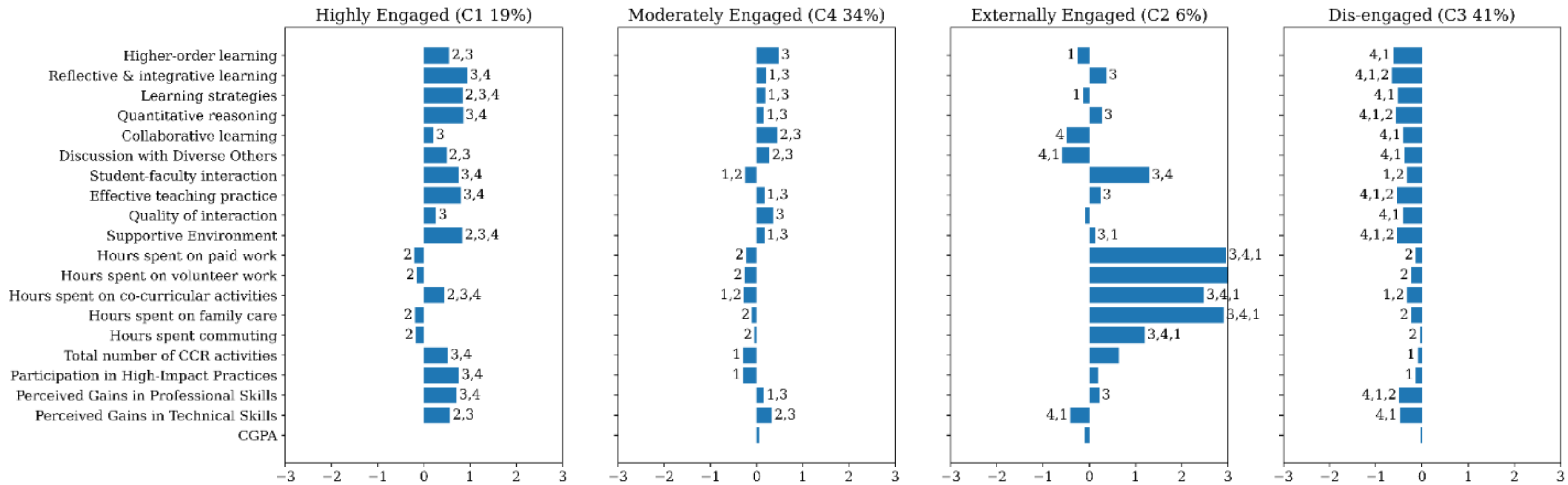

Figure 3. Averaged z-scores for the four clusters identified from the 2020 first-year student data

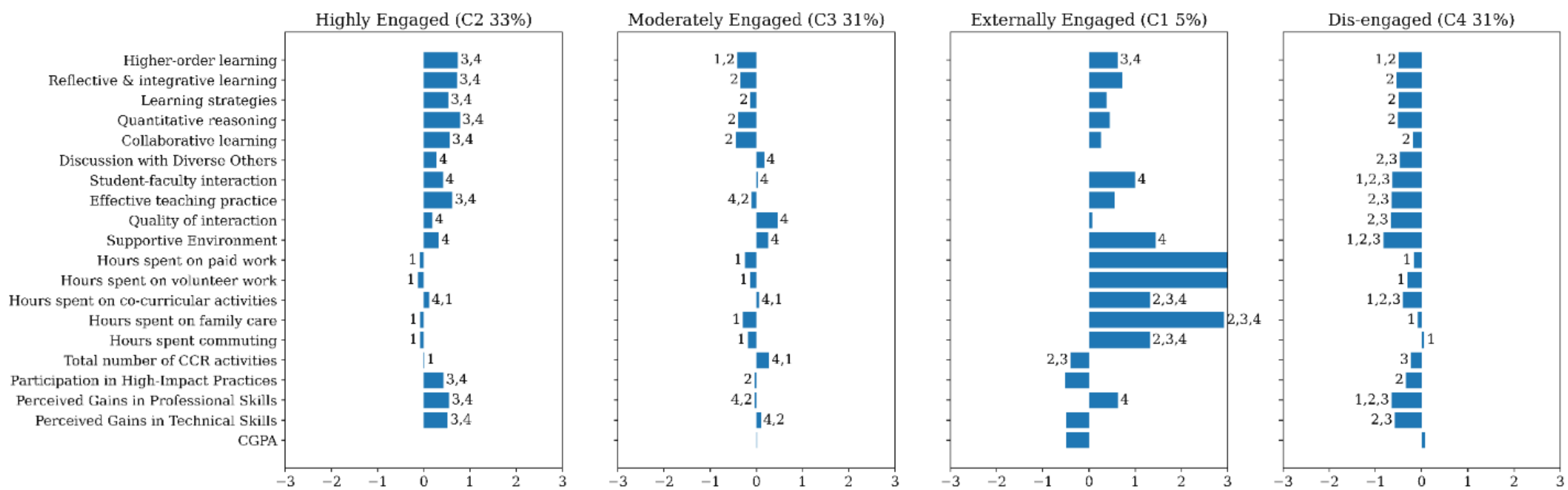

Figure 4. Averaged z-scores for the four clusters identified from the 2020 senior student data

5.2 Relationship between Student Clusters, and Learning Outcomes and Background

Hierarchical regression analysis was performed on each of the data sets to inspect the effect of student background variables (Model 1) and a combination of student background variables and four identified clusters (with Disengaged Learners as the reference group) (Model 2) on the four learning outcomes. Tables 2a to 2d present the summary of the results about these models.

As shown in the "Variance Difference" columns of these tables, it is evident that the identified student clusters explained around 20% or more variance in the learning outcomes of Perceived Gains in Professional Skills and Perceived Gains in Technical Skills whereas these clusters explained very little or no variance in GPA and retention in the second year (for the first-year students) or graduation with five years (for the senior students). This contrast suggests that the identified student clusters were better predictors for the two self-reported learning outcomes than the two "objective" learning outcomes.

Table 2a. Variance in learning outcomes explained by models *without* (model 1) and *with* (model 2) the four student clusters: *2017 first-year* student sample

Outcome Variables	Model 1	Model 2	Variance Difference
Perceived Gains in Professional Skills[a]	5.4%**	29.3%***	23.9%
Perceived Gains in Technical Skills[a]	2.1%	26.1%***	24.0%
GPA[a]	4.1%*	3.9%*	-.2%
Retention in the second year[b]	12.4%	13.5%***	1.1%

Variables entered into Model 1: gender, residential status, living arrangement, educational aspiration, race, sexual orientation, first-generation status, prior postsecondary experience, being an athlete, and age.
Variables entered into Model 2: All those variables for Model 1 and three dummy variables of student clusters, with Dis-engaged Learners as the reference group.

a. R squared is used to indicate variance explained. The ANOVA test was used to assess the linear regression models.
b. Cox & Snell R Square is used to indicate variable explained. The Chi-square test was used to assess the binary logistic regression model.

Significance level of the model: **p* < .05; ***p* < .01; ****p* < .001

Table 2b. Variance in learning outcomes explained by models *without* (model 1) and *with* (model 2) the four student clusters: *2017 senior* student sample

Outcome Variables	Model 1	Model 2	Variance Difference
Perceived Gains in Professional Skills[a]	2.9%	22.3%***	19.4%
Perceived Gains in Technical Skills[a]	2.9%	23.5%***	21.6%
GPA[a]	14.0%***	13.8%***	-0.2%
Graduation within five years[b]	10.2%*	11.5%*	1.3%

The same note for Table 2a applies to this table.

Table 2c. Variance in learning outcomes explained by models *without* (model 1) and *with* (model 2) the four student clusters: *2020 first-year* student sample

Outcome Variables	Model 1	Model 2	Variance Difference
Perceived Gains in Professional Skills[a]	5.7%**	24.7%***	19.0%
Perceived Gains in Technical Skills[a]	5.8%	27.3%***	21.5%
GPA[a]	10.1%***	9.9%***	-0.2%
Retention in the second year[b]	14.3%***	14.7%***	0.4%

The same note for Table 2a applies to this table.

Table 2d. Variance in learning outcomes explained by models *without* (model 1) and *with* (model 2) the four student clusters: *2020 senior* student sample

Outcome Variables	Model 1	Model 2	Variance Difference
Perceived Gains in Professional Skills[a]	3.0%	30.9%***	27.9%
Perceived Gains in Technical Skills[a]	4.0%	22.4%***	18.4%
GPA[a]	-0.3%	-.08%	-0.05%
Graduation within five years[b]	-	-	-

The same note for Table 2a applies to this table.
Additionally, analysis was not performed on the variable of "graduation within five years" as the number of students who did not graduate within five years was very small.

In addition, Tables 3a and 3b show the standardized regression coefficients (Beta values) of the cluster membership (with the Disengaged cluster as the reference) on two self-reported learning outcomes— Perceived Gains in Professional Skills and Perceived Gains in Technical Skills, when background variables were controlled for (i.e., Model 2). The Beta values for the Highly Engaged cluster ranged between .45 to .60 whereas the Beta values for the Moderately Engaged cluster ranged between .30 and .41 and those values for the Externally Engaged cluster were even lower, when the Beta values for the Disengaged cluster were set to 0. These results show that the "Highly Engaged" cluster membership made a greater contribution to both self-reported learning outcomes than the membership of "Moderately Engaged" or "Externally Engaged."

Table 3a. Contributions of four student clusters to two self-reported learning outcomes: 2017 data

	Perceived Gains in Professional Skills (Beta)		Perceived Gains in Technical Skills (Beta)	
	First-year	Senior	First-year	Senior
Highly Engaged	0.53***	0.47***	0.50***	0.45***
Moderately Engaged	0.30***	0.38***	0.40***	0.41***
Externally Engaged	0.24***	0.18**	0.07	0.01
Disengaged (reference)	-	-	-	-

*p < .05; **p < .01; ***p < .001
Control variables: gender, residential status, living arrangement, educational aspiration, race, sexual orientation, first-generation status, prior postsecondary experience, being an athlete, and age.

Table 3b. Contributions of four student clusters to two self-reported learning outcomes: 2020 data

	Perceived Gains in Professional Skills (Beta)		Perceived Gains in Technical Skills (Beta)	
	First-year	Senior	First-year	Senior
Highly Engaged	0.46***	0.60***	0.44***	0.52***
Moderately Engaged	0.31**	0.33***	0.39***	0.33***
Externally Engaged	0.13*	0.31***	-0.01	0.06
Disengaged (reference)	-	-	-	-

The same notes as Table 3a

A set of Chi-square tests were used to inspect the relationship between the identified student clusters and the following nine student background variables:

- Educational aspiration: expecting to complete some university or a Bachelor's degree, expecting to complete a Master's degree, or expecting to complete a doctoral or professional degree.
- Living arrangement: Living within a walking distance from campus, living farther than a walking distance from campus, or none of the above (e.g., taking online courses, or in transition).
- Being an athlete: whether or not being a student-athlete sponsored by the university's athletics department.
- Prior postsecondary experience: whether or not having attended another postsecondary institution before enrolment in the current program.
- Residential status: being an international student, being a permanent resident of Canada, or being a Canadian citizen.
- Sexual orientation: straight, LGBTQ, or no response
- Gender: man or women (binary institutional data)
- Race: white, Chinese, South Asian, East and Southeast Asian, West Asian and Arab, other racial identity, and multi-racial identity (some of these categories were created by combining multiple racial identities that had very small sample sizes).
- First-generation status: whether or not having the first-generation status (a derived variable by recoding a variable on parental education). First-generation means neither parent or anyone who raised the student holds a bachelor's degree.

Tables 4a to 4d present the variables that showed a statistically significant result from each of the four data sets, with Cramer's V as the effective size measure. Almost all the effect sizes were above .15, which is a general indicator for having an strong effect [46]. Given that the sample sizes were relatively small in this study, it is fair to say the effect sizes of the results in these tables were medium or above.

While each of the four data sets showed different variables that were significantly associated with the four student clusters, it is evident that Externally Engaged learners stood out as a prominent cluster that demonstrated distinctive relations with some of the nine background characteristics of the students in each sample. For example, within the 2017 first-year cohort, the

“Externally Engaged” learners were more likely to be those students who had an atypical living arrangement, had attended another postsecondary institution before enrolment in the current program, or were a student-athlete or a permanent resident of Canada. All these represented marginalized life situations.

Another noteworthy cluster was Highly Engaged learners, who were more likely to live within a walking distance from campus (Table 4a and 4b) and more likely to expect to complete a doctoral or professional degree (Tables 4b and 4c). These life situations offered advantages to the Highly Engaged learners.

Table 4a. Significant associations between student clusters and background: 2017 first-year sample

Variables	Chi-square statistics	df	Cramer's V	Distinctive features
Living arrangement	18.40**	6	.17	HE: more likely to live within a walking distance from campus (80% in HE vs. 70% in the total sample) EE: more likely to choose “None of above” (19% in EE vs. 6% in the total sample)
Being an athlete	18.27***	3	.23	EE: more likely to be an athlete (23% in EE vs. 7% in the total sample)
Prior postsecondary experience	18.69***	3	.23	EE: more likely to have attended another postsecondary institution before enrolment (41% in EE vs. 13% in the total sample)
Residential status	15.75*	6	.15	HE: more likely to be an international student (35% in HE vs. 22% in the total sample); ME: more likely to be a Canadian citizen (77% in ME vs. 66% in the total sample) EE: more like to be a permanent resident (23% in EE vs. 11% in the total sample)

Significance level: *$p < .05$; **$p < .01$; ***$p < .001$
Note: No statistical significance was found in the relations between student clusters and the variables of educational aspiration, sexual orientation, gender, race, and first-generation status, at the .05 level.

Table 4b. Significant associations between student clusters and background: 2017 senior student sample

Variables	Chi-square statistics	df	Cramer's V	Distinctive features
Educational aspiration	26.24***	6	.21	EE: more likely to aspire to have a Bachelor's degree (73% in EE vs. 41% in the total sample) HE: more likely to aspire to have a Doctoral degree (32% in HE vs. 20% in the total sample)
Living arrangement	14.34*	6	.15	HE: more likely to live within a walking distance from campus (68% in HE vs. 58% in the total sample) EE: more likely to choose "None of above" (23% in EE vs. 8% in the total sample)
Being an athlete	8.28*	3	.16	EE and HE: more likely to be athlete (14% in EE and 13% in HE vs. 7% in the total sample)
Residential status	19.75**	6	.18	EE: more likely to be an international student (41% in EE vs. 19% in the total sample)
Race	32.83*	18	.19	EE: more likely to be Chinese (46% in EE vs. 32% in the total sample)
First-generation	23.15***	3	.27	EE: more likely to be first-generation (55% in EE vs. 18% in the total sample)

Significance level: **p* < .05; ***p* < .01; ****p* < .001

Note: No statistical significance was found in the relations between student clusters and the variables of prior postsecondary experience, sexual orientation, and gender, at the .05 level.

Table 4c. Significant associations between student clusters and background: 2020 first-year student sample

Variables	Chi-square statistics	df	Cramer's V	Distinctive features
Educational aspiration	17.69**	6	.16	EE: more likely to aim to obtain a Bachelor's degree (65% in EE vs. 39% in the total sample) HE: more likely to aim to obtain a doctoral degree (31% in HE vs. 19% in the total sample)
Being an athlete	23.91***	3	.26	EE: more likely to be an athlete (30% in EE vs. 7% in the total sample)
Prior postsecondary experience	21.40***	3	.24	EE: more likely to have attended another postsecondary institution before enrolment (33% in EE vs. 8% in the total sample)
Residential status	14.67*	6	.14	EE: more likely to be an international student (38% in EE vs. 23% in the total sample)
First-generation	17.39**	3	.22	EE: more likely to have a first-generation status (52% in EE vs. 19% in the total sample)

Significance level: **p* < .05; ***p* < .01; ****p* < .001

Note: No statistical significance was found in the relations between student clusters and the variables of living arrangement, sexual orientation, gender, and race, at the .05 level.

Table 4d. Significant associations between student clusters and background: 2020 senior student sample

Variables	Chi-square statistics	df	Cramer's V	Distinctive features
Educational aspiration	20.56**	6	.21	EE: more like to expect to complete some university or a Bachelor's degree (55% in EE vs. 34% in the total sample)
Living arrangement	15.96*	6	.19	EE: more likely to choose "none of the above" (18% in EE vs. 2% in the total sample)
Prior postsecondary experience	14.22**	3	.25	EE: more likely to have attended another postsecondary institution before enrolment (46% in EE vs. 11% in the total sample)

Significance level: $*p < .05$; $**p < .01$; $***p < .001$
Note: No statistical significance was found in the relations between student clusters and the variables of being an athlete, residential status, sexual orientation, gender, race, first-generation status, at the .05 level.

5.3 Changes from First Year to Final Year

When the 2017 first-year data were linked to the 2020 senior student data, only 14 students were identified to have completed the two NSSE surveys with an interval of three years. A comparison of the cluster types of these students in the first year and the final year reveal the results presented in Table 5, when we ranked the four student clusters by the level of engagement from the lowest to the highest:

1. Disengaged learners;
2. Externally Engaged learners;
3. Moderately Engaged learners;
4. Highly Engaged learners.

Table 5 shows that the majority of this small group of students (71%) became more engaged learners in their final year, in comparison to their first year of studies. However, as this result was generated from a very small sample size, a further investigation was needed to identify some other patterns in our data.

Table 5. Shifts across clusters from the first year to the final year among the same students

Changes	n	%
No change	1	7%
Moved down to a lower-engagement cluster	3	21%
Moved up to a higher-engagement cluster	10	71%
Total	14	100%

We subsequently compared the senior student sample with the first-year student sample in the same cluster type to inspect whether any repeated patterns would emerge in both the 2017 and 2020 data sets. The full results of these comparisons are shown in Appendix C, with Cohen's d as the effect size measure. While these comparisons were made using cross-sectional data, the identified pattern could apply to a longitudinal data set.

One distinctive pattern is shown in Figure 5, which reveals a drop, from the first year to the final year, in the mean value of the responses to the two Campus Environment indicators: Quality of Interaction and Supportive Environment. In the total sample, this drop in the ratings of Quality of Interaction was a mean difference of 4.8 ($d = 0.45$) in 2017; and a mean difference of 1.14 ($d = 0.38$) in 2020; the drop in the ratings of Supportive Environment was a mean difference of 8.25 ($d = 0.68$) in 2017, and a mean difference of 7.01 ($d = 0.55$) in 2020. Furthermore, the decreased ratings in both of these engagement indicators were more prominent among Highly Engaged and Disengaged learners than the other two student types—Moderately Engaged and Externally Engaged learners. For example, in the 2017 data, the *d* values in the difference among Highly Engagement and Disengaged learners were 0.88 and 0.56 whereas the *d* values in the difference for the other two student types were 0.31 and 0.25. This cluster-specific pattern would not have been revealed if the comparison was only made to the total sample of the data.

Combining the patterns shown in Table 5 and Figure 5, we noted that although the overall engagement level among engineering students might have increased from the first year to the senior year, some of the engagement indicators—the two Campus Environment indicators in particular—appeared to drop considerably over the years during the studies, to varying extents among different engagement groups.

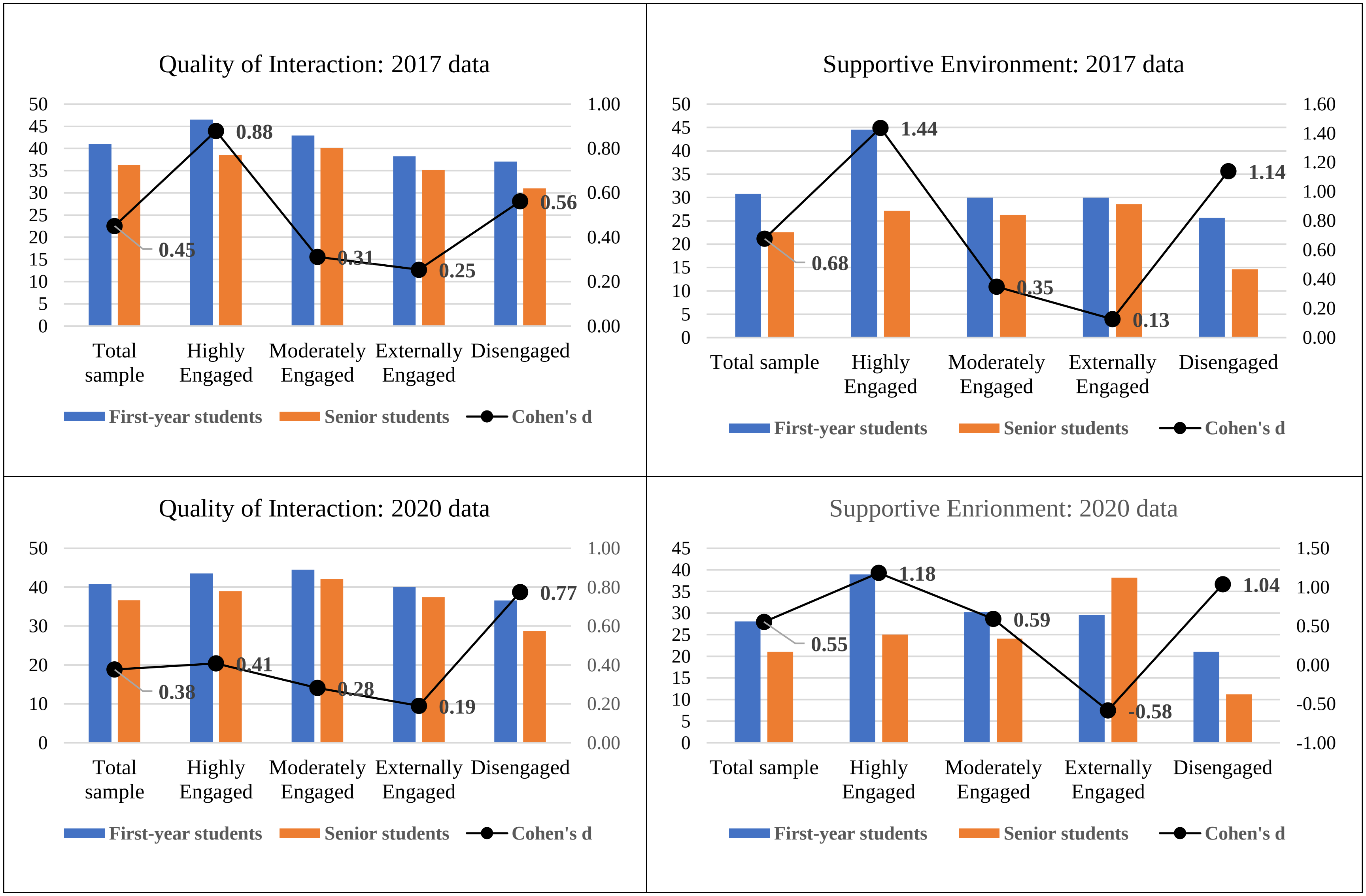

Figure 5. Comparisons between the first year and the final year in two Campus Environment indicators

6. Discussion and Conclusions

This study involved analysis of four data sets collected from engineering students in a Canadian engineering school in 2017 and 2020. The findings from our analyses offer insights on three inter-related themes: engagement-based student typology, equity and diversity in student typology, and student typology as a constructed type.

6.1. Engagement-Based Student Typology

Based on the selected variables that measured engineering students' curricular, co-curricular and extra-curricular experiences, our analysis identified four student clusters or types: Highly Engaged, Moderately Engaged, Externally Engaged, and Disengaged learners. This result was similar to previous studies that used NSSE data in cluster analysis [21, 22] in that a range of student types, including those who were disengaged, emerged from the analysis.

Another finding that aligned with the earlier study [21] was that the student typology identified from the NSSE survey data serves as a significant predictor for two self-reported learning outcomes—perceptions of gains in skill development (both technical and professional skills). Note that the student typology was identified entirely based on student experience variables. The finding that a higher engagement cluster membership was a significant predictor for the two self-reported learning outcomes corroborates the positive correlation between student engagement and perceived success [5, 25, 26]. However, interestingly our findings also revealed that the engagement-based student typology provided little explanation for directly assessed learning outcomes—student grades and retention or graduation. In fact, there was little to no correlations between the students' engagement indicators and CGPAs in all four data sets used in this study. Other studies also show that while student engagement measures in NSSE were positively correlated with students' GPAs, the correlations were weak [47]; and the effect of student engagement may be conditional upon other factors such as students' prior academic abilities [47] or psychological capital resources, such as efficacy, optimism and resilience [48]. We learned from our earlier study [49] that the average grades in the last four years of high school was a statistically significant predictor for engineering students' cumulative GPAs upon graduation and their graduation status. This gave us a reason for speculating that the effect of identified student typology on GPAs in the final year might be conditional upon students' high school grades.

In addition, our analysis identified four very similar engagement-based clusters or types based on the two sets of first-year and senior student samples (as reported earlier in Table 1), which suggests that an engagement-based student typology looked similar from the first year to the final year. However, the student types may be characterized by different levels of engagement. The two Campus Environment indicators were good examples to illustrate this pattern. While the mean scores of Quality of Interaction and Supportive Environment indicators for almost all the student types decreased from the first year to the final year, as shown in Figure 5, the nature of the four types of students remained almost the same. This suggests that a student typology was constructed in relative terms, and there would be no clear, absolute cut-off points to define who were highly engaged or disengaged. Therefore, while the four student types were labelled as Highly Engaged, Moderately Engaged, Externally Engaged, and Disengaged, we would caution against using these terms to characterize individual students who were assigned a membership as a result of our analysis. Rather, the identified typology informs an understanding that students engage in their academic, co-curricular and extracurricular activities in different ways and to varying extents. This may illustrate the difference of the “constructed type” versus the “existential type” highlighted by McKinney about constructive typology [44]. With this understanding about these constructed student types, educators and student support services can redesign experiences for their students to better serve the needs of students of each type in course offering and student programming.

Furthermore, the findings from our derived longitudinal student sample suggested that some of the students were likely to shift between engagement-based types from the first year to the final year. This shift may relate to the changes in students’ needs, expectations, and priorities during the course of their studies. A larger sample that is derived from linking different data sets on the same individuals would generate more solid evidence about the patterns associated with shifting across student types over time.

6.2.Equity and Diversity in a Student Typology

Our study is distinctive from the previous ones as our analysis uncovered the distinctive Externally Engaged learners, who constituted a small proportion of our samples but would well deserve a close examination. Our findings showed that this group of learners were most highly engaged in work (either paid or volunteering), co-curricular activities, family care or commuting. They were also more likely to have various life situations that could be atypical to the mainstream student population in an engineering school, such as having attended another postsecondary institution before enrolment in the current university, being an international student or a permanent resident, or being the first one in their family to participate in postsecondary education. As such, the Externally Engaged learners were a marginalized student type. This type emerged from our study partly because we included measures of co-curricular and extracurricular experiences into the cluster analysis. This decision was based on our belief that students learn and grow through activities in multiple contexts and situations. The life-wide learning perspective [50] proved to be useful for research on engagement-based typology.

Furthermore, our typology-focused analysis offered new insights on certain patterns about different types of students, which would not have been uncovered by taking an alternative, aggregate approach. For example, our comparisons of the ratings for the corresponding student type between the first year and final year data sets revealed that the drop in the two Campus Environment indicators was more prominent for Highly Engaged learners and Disengaged learners. Hopefully, this drop might not have much influence on the experiences of the Highly Engaged learners. However, the decreased ratings in the perceptions of the campus environment in the final year could have impacted the experiences of the Disengaged learners in significant ways. The practical implication from this would be that some student services may need to be allocated to support those students in the final year who are relatively disengaged with campus life.

6.3. Student Typology as the Constructed Type

In light of the framework of constructive typology, our experience in analyzing four data sets collected in two years with three years apart led us to the following interpretative claims about student typology:

- Student typology is a constructed type in that it is purposefully constructed, based on thoughtfully selected features, to better understand students' learning experiences and outcomes through comparisons of student types.
- The constructed student types, in contrast with an "existential type," may not correspond exactly to what happened to *individual* students in reality but can serve as a heuristic device to offer insights about differences in various student *groups*. They offer a way of knowing the student population.
- Student typology helps reveal the diversity in a student population, uncover hidden equity issues, and contributes to identifying which student groups may be marginalized.
- The typological procedure involved in the process of identifying a student typology promises an alternative method for analyzing highly dimensional data.

It should be noted that student typology research is not entirely new to engineering education researchers. Godwin and her colleagues recommended typological analysis as an approach to analyzing student data to identify patterns within engineering students' underlying attitudes, beliefs, and mindsets [51]. Our paper contributes to the literature on student typology by focusing on engagement or experience-based data, grounding the discussion in an existing theoretical framework of constructive typology, and extending its implications to equity, diversity and inclusion in engineering education.

6.4.Limitations and Future Work

As alluded to earlier, a major limitation in our study was the relatively small sample sizes in our data sets, which could have affected the predictive power of our statistical models. Constrained by the sample sizes, we were not able to derive a longitudinal data set that would include an adequate number of students who completed the NSSE instrument with an interval of three years. Therefore, we had to make analytical claims based on the existing cross-sectional data. Larger sample sizes in both years of data collection would make creating an adequate longitudinal data set possible.

Another limitation was our reliance on k-means cluster analysis as the analytical procedure for identifying a student typology. There are other cluster analysis methods, such as latent class analysis and Gaussian mixture modeling. While we did try out these methods in our analysis, they did not seem to offer us more insights than the results shown in this paper from k-means cluster analysis. Future work can focus on an exploration of other analytical methods than k-means clustering.

A third limitation involved the use of survey data on student engagement. It was possible that those students who were more engaged in their studies than others self-selected to complete the NSSE survey; and therefore, the survey responses were potentially more representative of those highly engaged than of those less engaged students. However, this limitation might exert little impact on the results about the student typology as the typology was constructed in relative terms.

Finally, while the four data sets in this study offered the advantage of comparing results from different data sets, they also allowed us to see differences in the results based on different data sets when the same analytical procedure was implemented. For example, the 2020 senior student sample seemed to generate patterns that looked somewhat different from the other three samples. It is possible that these differences were ascribed to the variations in the responses provided by different student cohorts. When examining these variations, we drew conclusions on the basis of the repeated patterns in different data sets. These repeated patterns offer us greater confidence in making the claims discussed in this paper about engagement-based student typology.

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Appendix A. Variables included for analysis

Table A1. Student experience variables

Categories of variables*	Measurement	Range
Academic Challenge /Academic Engagement	Higher-order learning	0 to 60
	Reflective & integrative learning	0 to 60
	Learning strategies	0 to 60
	Quantitative reasoning	0 to 60
Learning with Peers	Collaborative Learning	0 to 60
	Discussions with diverse others	0 to 60
Experiences with Faculty	Student-faculty interaction	0 to 60
	Effective teaching practice	0 to 60
Campus Environment	Quality of interaction	0 to 60
	Supportive Environment	0 to 60
Co- / Extra-curricular Experiences	Hours spent on paid work (on and off campus) in a week	0 to 66
	Hours spent doing volunteer work in a week	0 to 33
	Hours spent participating in co-curricular activities in a week	0 to 33
	Total number of Co-curricular Record activities a student undertook up to the time of NSSE administration	0 to 9
	Hours spent on family care in a week	0 to 33
	Hours spent commuting in a week	0 to 33
Engagement with High-Impact Practices	Total number of High-Impact Practices students participated in	0 to 6

*The categorization of these variables is based on NSSE Engagement Indicators.

Table A2: Learning outcome variables

Category	Measurement	Range
Learning outcomes	Perceived Gains in Professional Skills, derived by averaging existing responses to five variables: pgwrite, pgspeak, pgvalues, pgdiverse, pgcitizen	1 to 4
	Perceived Gains in Technical Skills, derived by averaging existing responses to four variables: pgthink, pganalyze, pgwork, and pgprobsolve	1 to 4
	Cumulative GPA	0 to 4
	Second-year retention	0 or 1
	Graduation within 5 years	0 or 1

Appendix B. Comparisons of standardized scores of each variable by identified clusters

Table B1. Clusters identified from first-year student data in 2017

Categories	Variables	Highly Engaged (n=57, 17%)	Moderately Engaged (n=134, 39%)	Externally Engaged (n=22, 6%)	Disengaged (n=128, 38%)	Welch statistic	eta squared
Academic Challenge /Academic Engagement	Higher-order learning	0.80	0.26	-0.53	-0.54	42.61	0.26
	Reflective & integrative learning	0.81	0.28	0.29	-0.70	61.79	0.33
	Learning strategies	0.83	0.19	0.11	-0.59	39.78	0.26
	Quantitative reasoning	0.89	0.11	0.19	-0.54	41.06	0.25
Learning with Peers	Collaborative Learning	0.29	0.40	0.06	-0.56	26.63	0.20
	Discussions with diverse others	0.40	0.42	-0.48	-0.53	29.22	0.22
Experiences with Faculty	Student-faculty interaction	1.05	-0.20	0.97	-0.42	39.90	0.33
	Effective teaching practice	1.04	-0.02	-0.21	-0.41	43.63	0.25
Campus Environment	Quality of interaction	0.50	0.17	-0.25	-0.36	12.84	0.11
	Supportive Environment	1.09	-0.07	-0.06	-0.40	35.55	0.26
Co- / Extra-curricular Experiences	Hours spent on paid work (on and off campus) in a week	-0.21	-0.28	3.54	-0.23	20103.73	0.87
	Hours spent doing volunteer work in a week	0.39	-0.34	2.53	-0.25	84.82	0.51
	Hours spent participating in co-curricular activities in a week	0.54	-0.30	1.97	-0.26	50.73	0.36
	Total number of CCR activities a student undertook up to spring 2017	0.48	-0.08	0.13	-0.16	4.25	0.05
	Hours spent on family care in a week	-0.18	-0.26	2.76	-0.12	43.97	0.53
	Hours spent commuting in a week	-0.24	-0.19	1.69	0.02	43.37	0.21
Engagement with High-Impact Practices	Participation in High-Impact Practices	0.04	0.28	0.08	-0.33	8.92	0.07

All variables: $p < .001$.

Table B2. Clusters identified from senior student data in 2017

Categories	Variables	Highly Engaged (n=63, 20%)	Moderately Engaged (n=116, 37%)	Externally Engaged (n=22, 7%)	Dis-engaged (n=109, 35%)	Welch statistics	Eta squared
Academic Challenge /Academic Engagement	Higher-order learning	0.51	0.35	-0.29	-0.61	34.80	0.24
	Reflective & integrative learning	0.70	0.20	0.38	-0.70	41.90	0.30
	Learning strategies	0.51	0.28	0.17	-0.63	27.76	0.22
	Quantitative reasoning	0.73	0.21	0.09	-0.66	40.05	0.28
Learning with Peers	Collaborative Learning	0.57	0.05	-0.32	-0.32	10.68	0.11
	Discussions with diverse others	0.76	-0.33	-0.23	-0.04	32.47	0.16
Experiences with Faculty	Student-faculty interaction	0.74	-0.06	0.87	-0.54	33.08	0.27
	Effective teaching practice	0.17	0.57	0.40	-0.79	66.54	0.36
Campus Environment	Quality of interaction	0.22	0.38	-0.11	-0.51	17.85	0.16
	Supportive Environment	0.39	0.32	0.52	-0.68	39.57	0.25
Co- / Extra-curricular Experiences	Hours spent on paid work (on and off campus) in a week	-0.27	-0.21	3.01	-0.22	217.80	0.69
	Hours spent doing volunteer work in a week	-0.11	-0.27	3.05	-0.26	49.19	0.71
	Hours spent participating in co-curricular activities in a week	0.51	-0.40	1.58	-0.18	70.07	0.30
	Total number of CCR activities a student undertook up to spring 2017	0.92	-0.28	0.18	-0.27	13.23	0.19
	Hours spent on family care in a week	-0.19	-0.22	2.58	-0.17	25.99	0.23
	Hours spent commuting in a week	-0.38	-0.21	1.36	0.17	20.41	0.51
Engagement with High-Impact Practices	Participation in High-Impact Practices	0.81	-0.13	-0.98	-0.14	25.18	0.22

All variables: $p < .001$.

Table B3. Clusters identified from first-year student data in 2020

Categories	Variables	Highly Engaged (n=63, 20%)	Moderately Engaged (n=116, 37%)	Externally Engaged (n=22, 7%)	Dis-engaged (n=109, 35%)	Welch statistics	Eta squared
Academic Challenge /Academic Engagement	Higher-order learning	0.51	0.35	-0.29	-0.61	34.80	0.24
	Reflective & integrative learning	0.70	0.20	0.38	-0.70	41.90	0.30
	Learning strategies	0.51	0.28	0.17	-0.63	27.76	0.22
	Quantitative reasoning	0.73	0.21	0.09	-0.66	40.05	0.28
Learning with Peers	Collaborative Learning	0.57	0.05	-0.32	-0.32	10.68	0.11
	Discussions with diverse others	0.76	-0.33	-0.23	-0.04	32.47	0.16
Experiences with Faculty	Student-faculty interaction	0.74	-0.06	0.87	-0.54	33.08	0.27
	Effective teaching practice	0.17	0.57	0.40	-0.79	66.54	0.36
Campus Environment	Quality of interaction	0.22	0.38	-0.11	-0.51	17.85	0.16
	Supportive Environment	0.39	0.32	0.52	-0.68	39.57	0.25
Co- / Extra-curricular Experiences	Hours spent on paid work (on and off campus) in a week	-0.27	-0.21	3.01	-0.22	217.80	0.69
	Hours spent doing volunteer work in a week	-0.11	-0.27	3.05	-0.26	49.19	0.71
	Hours spent participating in co-curricular activities in a week	0.51	-0.40	1.58	-0.18	70.07	0.30
	Total number of CCR activities a student undertook up to spring 2020	0.92	-0.28	0.18	-0.27	13.23	0.19
	Hours spent on family care in a week	-0.19	-0.22	2.58	-0.17	25.99	0.23
	Hours spent commuting in a week	-0.38	-0.21	1.36	0.17	20.41	0.51
Engagement with High-Impact Practices	Participation in High-Impact Practices	0.81	-0.13	-0.98	-0.14	25.18	0.22

All variables: $p < .001$.

Table B4. Clusters identified from senior student data in 2020

Categories	Variables	Highly Engaged (n=70, 19%)	Moderately Engaged (n=127, 34%)	Externally Engaged (n=22, 6%)	Dis-engaged (n=152, 41%)	Welch	eta squared
Academic Challenge /Academic Engagement	Higher-order learning	0.55	0.48	-0.25	-0.62	55.56	0.30
	Reflective & integrative learning	0.94	0.20	0.37	-0.65	72.68	0.36
	Learning strategies	0.84	0.19	-0.13	-0.52	46.01	0.26
	Quantitative reasoning	0.85	0.16	0.27	-0.56	45.57	0.28
Learning with Peers	Collaborative Learning	0.21	0.45	-0.49	-0.40	23.94	0.16
	Discussions with diverse others	0.49	0.28	-0.58	-0.38	21.28	0.15
Experiences with Faculty	Student-faculty interaction	0.75	-0.25	1.30	-0.33	35.20	0.27
	Effective teaching practice	0.80	0.17	0.24	-0.55	43.17	0.26
Campus Environment	Quality of interaction	0.26	0.36	-0.08	-0.41	17.52	0.12
	Supportive Environment	0.83	0.17	0.12	-0.54	40.84	0.26
Co- / Extra-curricular Experiences	Hours spent on paid work (on and off campus) in a week	-0.21	-0.23	2.96	-0.14	25.07	0.56
	Hours spent doing volunteer work in a week	-0.15	-0.26	3.63	-0.24	103.68	0.84
	Hours spent participating in co-curricular activities in a week	0.44	-0.27	2.48	-0.33	58.43	0.47
	Total number of CCR activities a student undertook up to spring 2020	0.51	-0.29	0.64	-0.09	11.82	0.11
	Hours spent on family care in a week	-0.20	-0.10	2.90	-0.24	39.66	0.54
	Hours spent commuting in a week	-0.18	-0.05	1.20	-0.05	6.98	0.09
Engagement with High-Impact Practices	Participation in High-Impact Practices	0.76	-0.29	0.19	-0.13	17.55	0.15

All variables: $p < .001$.

Appendix C. Differences between first-year and senior students in the same cluster

2017 data

Variables	Total sample		Highly Engaged		Moderately Engaged		Externally Engaged		Disengaged	
	Mean diff.	Cohen's d	Mean diff.	Cohen's d	Mean diff.	Cohen's d	Mean diff.	Cohen's d	Mean diff.	Cohen's d
Perceived gains in professional skills	-0.02	-0.03	**0.24***	0.36	**-0.18***	-0.30	0.02	0.03	0.07	0.11
Perceived gains in technical skills	**-0.12****	-0.19	-0.04	-0.08	**-0.13***	-0.25	0.10	0.15	**-0.14***	-0.24
CGPA	**-0.29*****	-0.43	**-0.40*****	-0.67	**-0.19***	-0.28	-0.31	-0.45	**-0.33*****	-0.49
Higher-order learning	**4.74*****	0.39	**8.19*****	0.86	**3.57****	0.33	1.82	0.13	**5.71*****	0.56
Reflective & integrative learning	-0.48	-0.05	0.94	0.10	0.40	0.05	-1.36	-0.10	-0.75	-0.09
Learning strategies	-0.07	-0.01	4.14	0.30	-1.35	-0.11	-0.95	-0.08	0.62	0.05
Quantitative reasoning	**-5.56*****	-0.40	-3.33	-0.30	**-6.96*****	-0.55	-4.18	-0.34	**-3.90****	-0.32
Collaborative Learning	0.19	0.01	-3.39	-0.27	**4.50****	0.42	5.00	0.38	**-2.71***	-0.23
Discussions with diverse others	-0.64	-0.04	**-4.67***	-0.42	**10.26*****	0.81	-5.00	-0.38	**-8.32*****	-0.58
Student-faculty interaction	-2.63	-0.20	0.91	0.07	**-4.43****	-0.40	-1.82	-0.11	-0.78	-0.09
Effective teaching practice	**1.79***	0.15	**11.39*****	1.14	**-5.20*****	-0.52	-5.41	-0.45	**6.59*****	0.75
Quality of interaction	**4.77*****	0.45	**8.00*****	0.88	**2.81****	0.31	3.14	0.25	**5.99*****	0.56
Supportive Environment	**8.25*****	0.68	**17.38*****	1.44	**3.64****	0.35	1.41	0.13	**11.04*****	1.14
Hours spent on paid work (on and off campus) in a week	**-1.37***	-0.16	-0.65	-0.19	**-1.66*****	-0.46	0.00	0.00	**-1.17***	-0.25
Hours spent doing volunteer work in a week	-0.38	-0.08	**1.74***	0.45	-0.31	-0.19	**-6.14*****	-1.16	-0.04	-0.02
Hours spent participating in co-curricular activities in a week	**-1.13***	-0.18	-1.64	-0.25	-0.05	-0.01	-1.05	-0.22	**-1.31***	-0.23

Total number of CCR activities a student undertook up to spring 2017	**-0.31*** **	-0.33	**-1.15*** **	-0.81	-0.01	-0.02	-0.45	-0.42	-0.07	-0.12
Hours spent on family care in a week	0.16	0.04	0.16	0.06	-0.08	-0.04	1.64	0.28	0.37	0.11
Hours spent commuting in a week	**-0.89***	-0.16	0.16	0.04	-0.60	-0.12	-0.45	-0.09	**-1.82****	-0.33
Participation in High-Impact Practices	**-2.10*** **	-2.12	**-3.13*** **	-3.45	**-1.77*** **	-2.00	**-0.77***	-0.67	**-2.11*** **	-2.48

Note: Mean difference = Value in the first year – Value in the final year. Therefore, a negative difference means an increase; and a positive difference means a decrease.

2020 data

Variables	**Total sample**		**Highly Engaged**		**Moderately Engaged**		**Externally Engaged**		**Disengaged**	
	Mean diff.	Cohen's d	Mean Diff.	Cohen's d	Mean Diff.	Cohen's d	Mean Diff.	Cohen's d	Mean Diff.	Cohen's d
Perceived gains in professional skills	0.03	0.04	0.15	0.25	**0.16***	0.26	-0.25	-0.34	0.12	0.20
Perceived gains in technical skills	**-0.11***	-0.17	-0.07	-0.12	0.04	0.08	-0.06	-0.07	-0.05	-0.08
CGPA	**-0.14****	-0.23	-0.13	-0.23	-0.11	-0.18	0.06	0.10	**-0.20****	-0.33
Higher-order learning	**4.51*** **	0.38	2.21	0.23	**14.85*** **	1.55	-5.68	-0.42	**3.07***	0.33
Reflective & integrative learning	**1.87***	0.18	**4.31****	0.55	**7.49*** **	0.98	-1.77	-0.12	0.64	0.08
Learning strategies	1.05	0.07	**5.75****	0.47	**5.65****	0.43	-6.23	-0.46	0.47	0.04
Quantitative reasoning	**-2.65***	-0.18	-1.41	-0.11	**5.21****	0.47	-5.18	-0.35	**-3.49***	-0.29
Collaborative Learning	**2.11***	0.17	-2.40	-0.22	**13.16*** **	1.29	-7.05	-0.48	-0.25	-0.02
Discussions with diverse others	**5.38*** **	0.37	**7.51*** **	0.58	**6.46*** **	0.53	-2.50	-0.15	**7.77*** **	0.53
Student-faculty interaction	-0.05	0.00	**5.12***	0.36	**-3.83****	-0.36	5.45	0.39	**3.30****	0.34
Effective teaching practice	-1.18	-0.11	0.32	0.03	1.93	0.21	-4.91	-0.33	0.35	0.04

Quality of interaction	**4.14*** **	0.38	**4.53** **	0.41	**2.39***	0.28	2.55	0.19	**7.89*** **	0.77
Supportive Environment	**7.01*** **	0.55	**13.94*** **	1.18	**6.14*** **	0.59	-8.59	-0.58	**9.79*** **	1.04
Hours spent on paid work (on and off campus) in a week	-0.70	-0.10	-1.49	-0.32	-0.44	-0.15	-5.27	-0.51	-0.40	-0.08
Hours spent doing volunteer work in a week	-0.08	-0.02	-0.15	-0.07	**-0.62***	-0.33	-0.36	-0.09	0.15	0.11
Hours spent participating in co-curricular activities in a week	**-1.24***	-0.19	0.42	0.07	**-3.28** **	-0.57	3.73	0.59	-0.32	-0.08
Total number of CCR activities a student undertook up to spring 2017	**0.16*** **	0.26	**0.52*** **	0.79	**-0.16** **	-0.40	**0.77***	0.61	**0.19*** **	0.39
Hours spent on family care in a week	-0.22	-0.05	-0.79	-0.25	**0.64***	0.21	-0.55	-0.09	**-0.92***	-0.32
Hours spent commuting in a week	-0.14	-0.02	-0.73	-0.14	0.58	0.11	-0.68	-0.09	-0.77	-0.13
Participation in High-Impact Practices	**-2.14*** **	-2.27	**-2.21*** **	-2.44	**-2.27*** **	-2.67	**-1.36***	-0.96	**-1.79*** **	-2.20

Note: Mean difference = Value in the first year – Value in the final year. Therefore, a negative difference means an increase; and a positive difference means a decrease.