Engineering Student Motivation and Perceived Metacognition in Learning Communities

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Engineering Student Motivation and Perceived Metacognition in Living-Learning Communities

Abstract

The effect of living-learning communities on students' motivation in engineering and their perceived use of metacognitive strategies were evaluated for first year engineering students using quantitative methods. There were two living-learning communities studied: an honors community and a science and engineering community. Students in both communities were enrolled in specific sections of an introductory engineering course designated for them. Students were surveyed at the beginning and end of their first semester on campus while enrolled in the course. The survey used was assessed for construct validity using a series of factor analyses. There were several distinctions between the motivational profiles of students' based on course section type (honors community, science and engineering community, and non-restricted sections of the course). The honors community seems to be attracting their targeted group of students, as students with higher mastery orientation and higher perceptions of their knowledge of cognition. Students in the science and engineering community were not significantly different than those in the non-restricted sections of the course at the beginning of the semester, but did have higher expectancies of success in their engineering course at the end of the semester.

Introduction

A living-learning community (LC) is defined as a group of students that, "1) live together on campus, 2) take part in a shared academic endeavor, 3) use resources in their residence environment designed specifically for them, and 4) have structured social activities in their residential environment that stress academics".[1(p10)] The first intentional LC, known as the experimental college, was created by Alexander Meiklejohn at the University of Wisconsin from 1927 to 1932. These communities became more common during the expansion of higher education in the 1950s and 1960s.[2] Over the years, several variations of LCs have been implemented in universities throughout the United States to improve undergraduate educational experiences and are today considered to be a high-impact practice in higher education.[3]

A LC is a type of community of practice, defined as a group of people engaging in collective learning in a shared domain. These communities have been shown to have positive effects on student integration, engagement, academic success, and persistence[1,2,4]; however, little research has examined how LCs influence factors in the affective domain. Within a community of practice there exist shared cultures, values, and goals, suggesting that LCs may influence these factors that lie within the affective domain.

The goals of this research are to: 1) validate a survey instrument to assess student motivation and perceived use of metacognitive strategies and 2) examine the differences between engineering students at a land grant institution in the southeastern US participating in one of two LCs and engineering students not participating in an LC using the validated survey instrument. This quantitative study was conducted using an 82 item survey to evaluate student perceptions twice during their first semester. Responses were compared within the semester to evaluate variations in motivations and changes over time based on participation involvement in LCs, and were also compared to a similar cohort of students who did not participate in LCs.

Living-Learning Communities

In the two LCs analyzed in this study, students both live together in a residence hall and take specific classes together. Both LCs have dedicated study space in the basement of the residence halls, have faculty member presence in the dorm, and hold extra-curricular activities to promote student engagement and community growth. However, both LCs differ in terms of academic requirements for admittance to the program, resources available to the participants, and program goals.

The honors LC (HC) has an interdisciplinary focus and is open to students in any major who meet minimum academic requirements. The mission of the HC at this institution is "to foster continued intellectual growth, to cultivate a lifelong respect for learning, and to prepare students for lives as leaders and change-agents"[5]. Completion of the honors program requirements earns students a distinction on their academic record. Each year, approximately 300 students are admitted to the HC at this institution from all majors, with approximately 75 of those students entering the College of Engineering and Science. HC students are required to take at least one honors section of a class each semester where all students in the class are part of the honors college. Honors sections have slightly more stringent requirements than their non-honors equivalent of the class. For example, students may cover more course material throughout the semester or require a research project as part of the course.

The science and engineering living-learning community (SEC) has an intradisciplinary focus and is only open to students pursuing degrees in science or engineering majors. The mission of the SEC is "to assist students in their transition to college and prepare them for their future academic and professional career by promoting: academic preparedness, professional development, interpersonal development, and community engagement"[5]. This year, approximately 400 students at this institution were admitted to the SEC. Students participating in the SEC enroll in SEC specific sections of courses required for their major when available. This year SEC sections were available for two classes which also have honors sections and regular sections. SEC sections of a class have the same academic requirements of regular sections, but all students in the class live in the same residence hall. The SEC also holds tutoring sessions in the residence hall for the two classes.

Frameworks

For this work, student motivation is considered to be structured from 1) higher-level long-term goals that are semi-stable traits of the individual and 2) task-specific motivations that vary from task to task. To examine these levels of motivation and their interconnections, several relevant motivational theories were utilized to evaluate student motivations toward long-term goals and short-term tasks.

One model for understanding how student motivation influences learning is the Motivated Action Theory presented by DeShon and Gillespie.[6] This model posits that students are driven to perform actions by goals that are situated in different levels or time scales, from goals that are long-term and stable, to goals that are temporary and situated in the present. The students' unique combinations of motivations toward long-term and short-term goals prompt students to act in certain ways.

Motivations Towards Long-Term Goals

Expectancy x Value

Students' motivations toward long-term goals are evaluated through Expectancy x Value theory, which focuses on the expectation of how one will perform on a task and how much one values a task or its outcomes.[7] Expectancy x Value theory posits that three main criteria must be met for motivated action: a) With enough effort, the performance can be achieved; b) If achieved, performance will lead to desired outcomes; and c) Those outcomes will lead to satisfaction.[7] Research applying Expectancy x Value theory has shown that engineering students who have higher expectations will have better academic performance[8], and those who see higher value for a task will persist longer.[7] Expectancy x Value theory has been developed to examine students' motivations toward long-term goals at a degree or course level.[7]

Expectancy was operationalized to assess how students expected to do in an introductory engineering course. Survey items evaluating expectancy include, "I expect to do well in this engineering course" and, "I am confident I can do an excellent job on the assignments and tests in this engineering course".

Future Time Perspective

Different motivational constructs have been used under the achievement motivation umbrella to examine the influence of motivation on engineering student academic performance.[9] Husman and Lens have expanded these frameworks to include the factor of time, examining students' perceptions of the future and how the future relates to present tasks.[10] Future Time Perspective (FTP) posits that the temporal distance of student goals paired with the perceived instrumentality of a current task, will influence student actions in the present [10]. FTP research has shown that students who have stronger academic motivations often have stronger or more detailed perceptions of the future and its impact on academic goals, which correlates to improved persistence and performance on academic tasks.[10] The FTP framework explicitly examines students' long-term goals, and is appropriate for application in examining engineering students' motivation.[11–13]

The FTP theoretical framework was operationalized to assess students' perceptions of the present and future in relation to their engineering degrees and their desire to be engineers. For this work, it was assumed that all students who have entered into a college-level engineering program consider graduating with a degree to be part of their future; thus, the time point of graduation was chosen as the future time point under consideration. Students' perceptions of the present were evaluated in terms of how their views of the engineering field were guiding their views of their current engineering course. Students' perceptions of the future were evaluated in terms of how first-year students viewed the future in relation to their engineering degree and their desire to be an engineer. Survey items evaluating future perceptions include, "My interest in engineering outweighs any disadvantages I can think of", and "I want to be an engineer". Survey items evaluating present perceptions include, "I will use the information I learn in this engineering course in the future" and, "What I learn in my engineering course will be important for my future occupational success".

Task-Level Motivations

Self-efficacy

Bandura's work in self-efficacy examines motivations toward short-term tasks.[14] Self-efficacy speaks to students' specific perceptions on how they will perform on a task.[15] Self-efficacy has been shown to influence the use of learning strategies on tasks related to students' courses.[16] While self-efficacy and expectancy are correlated constructs when examining goals with the same time scale[8], self-efficacy was developed to examine short-term tasks that require a high level of granularity[17] and makes it more useful for examining motivations toward short-term goals.

For this work, problem solving items were adapted from the Attitudes and Approaches to Problem Solving survey[18] to appropriately assess student self-efficacy for various problem solving tasks, and were then placed on a scale from 0-100.[17] This change allows us to examine motivation toward problem solving tasks (short-term tasks) that are distinct from motivation related to students' goal of obtaining an engineering degree (long-term goals).[6] Using the 100 point scale rather than a 5-point Likert scale allows us to get better gradation of student responses for a detail oriented tasks.[17] Survey items assessing problem solving self-efficacy asked students to "Please rate how certain you are that you can do each of the things listed below" followed by items such as "Drawing pictures or diagrams to answer multiple-choice engineering problems" and "Checking my work for errors when I have obtained an unreasonable solution".

Goal orientation

The literature describes three types of goal orientation: mastery approach, performance approach,[19] and work avoid.[20] Mastery goal orientation is defined as holding knowledge and understanding as the main purpose for learning, while performance approach goal orientation focuses on positive judgment from others as the main purpose for learning.[21] Studies have shown that both mastery and performance approach goals can be linked to "outcomes of motivation, affect, strategy use, and performance".[20] In a study examining achievement goals' effect on college students' success, performance approach goals and course performance were correlated while mastery goals were shown to correlate with continued subject interest.[22] Another distinct type of goal orientation, which applies to students, is work avoidance orientation.[23–25] Students with a work avoidance goal orientation prefer to work on academic tasks that are easy and can be completed in a short amount of time. [25] Specifically, work avoidance oriented students look to evade work and are not concerned with the views of others. Students with work avoidance goal orientation try to minimize their effort for academic tasks, and this type of orientation has been linked with "poor academic outcomes".[25] Research applying goal orientation frameworks often do not consider the timeframe that students are operating within, and more often consider goals that are only proximal in time.

For this work, goal orientation items were adapted from the work of Shell and Husman (2008).[26] These items were originally created by Schraw, Horn, Thorndike-Christ, and Bruning (1995)[27] and then adapted to be measured using a scale developed by Dweck[21]. Survey items spanning the constructs of mastery approach, performance approach, and work avoidance goal orientations asked students to "Use the scale given (5 point Likert-type) to rate how important achieving each of the following is to you in this class from Very Unimportant to Very Important" followed by items such as, "Really understanding this course's material", "Remembering enough from this class to impress people", and "Not having to work too hard in this class". Shell and Husman used these items in a study on undergraduates at a large Southwestern university in which they studied the connection between the dimensions of control and the different goal orientations. In this work it was shown that mastery goal orientation contributes to knowledge building/surface learning, while work avoidance orientation contributes to learned helplessness.[26]

Metacognition

Like motivation, metacognition has been shown to play an important role on problem solving performance, a key goal of many engineering programs.[28,29] The level of knowledge one has about their own thinking processes and their ability to regulate those processes describes their level of metacognition.[30] Metacognitive tasks have a broad impact on problem solving performance because these higher-level executive functions such as planning, monitoring, evaluating, and revising guide problem solving processes and are vital in monitoring progress towards goals.[31] Students using limited metacognitive processes typically are unable to identify and correct errors in problem solving attempts. Metacognitive tasks have been shown to be correlated to successful problem solving attempts.[28] There are two distinct components of metacognition: knowledge about cognition and regulation of cognition. Knowledge of cognition refers to the reflective aspect of metacognition and includes three components: declarative knowledge (knowledge about self and about strategies), procedural knowledge (knowledge about how to use strategies), and conditional knowledge (knowledge about when and why to use strategies).[32] Knowledge of cognition has been shown to play a key role in decision making and performance.[33–35] Regulation of cognition refers to an individual's ongoing cognitive processes and includes five skills: planning, information management strategies, comprehension monitoring, debugging strategies, and evaluation. These skills have been suggested to play a critical role in problem solving as they allow learners to organize and monitor their thinking.[35]

Metacognition was operationalized in this work to assess students' perceptions of their ability to use metacognitive strategies when solving an engineering problem. Items were adapted from Lee et al.'s (2009) work originally used to assess elementary students' use of metacognition when solving an everyday problem, which were originally based on Schraw and Dennison's work.[32]

Survey items to assess students' perceptions of their ability to use metacognitive strategies asked students to "Please rate your agreement for each item on a scale from Strongly Disagree to

Strongly Agree. When solving an engineering problem…" followed by items such as, "I think I know whether I have understood the problem well" and "I try to think in the ways that have worked in the past". It is important to note that we are measuring student's perceptions of their use of metacognition and not their metacognition because we are not directly observing their use of metacognitive skills as they solve problems.

Methods

Participants

Students enrolled in a first-year engineering (FYE) course at a southeastern land grant university participated in this study. This included five sections taken by students of an honors community (HC), seven sections taken by students of a science and engineering community (SEC), and eleven sections taken by students not involved in an LC.

A survey was administered (described in the subsequent section) at the beginning and end of the Fall 2013 semester to all students in the FYE course. There were 11 weeks between administrations of the survey. Of the 1094 students surveyed at the beginning of the Fall of 2013, 297 were in the SEC, 126 were in the HC, and 671 were in other sections open to all engineering students. A total of 880 students completed the survey at the end of the Fall 2013 semester with 227 students in the SEC, 123 students in the HC, and 509 students in other sections open to all engineering students. The difference in responses at the beginning and end of the semester is in part due to the number of students who withdrew from the course (approximately 18%). We were able to match 640 of the beginning of the semester responses to the end of the semester responses. This includes 156 students in the SEC, 98 students in the HC, and 384 students in other sections open to all engineering students. The discrepancy in matched surveys is due to students choosing to not report identifying information such as student ID number when they filled out the surveys.

Survey

The 82-item survey included items on motivation (goal orientation, self-efficacy, FTP, and expectancy-value) and metacognition (knowledge of cognition and regulation of cognition) as described in the theoretical frameworks section above. Items were five point, anchored Likert-type items except self-efficacy items, which were on a 100 point response scale. The survey was broken down into four sections as outlined in

Table 1. Part I included items related to goal orientation which included 3 constructs: performance approach, mastery, and work avoidance. Part II of the survey asked students questions related to their attitudes and beliefs about their experiences in their current engineering course and in their major, including Expectancy and Future Time Perspective items. Part III of the survey asked students to reflect on the metacognitive processes they use when solving an engineering problem. Part IV asked students to rate their confidence in doing problem solving

related tasks when solving an engineering problem as a means to assess students' problem solving self-efficacy.

Table 1: Summary of the frameworks and constructs included in each part of the original survey.

	Frameworks	**Constructs (# items)**
Part I	Goal Orientation	Mastery (5)
		Performance approach (5)
		Work avoidance (3)
Part II	Expectancy x Value	Expectancy (11)
	Future Time Perspective	Present perceptions of engineering (10)
		Future perceptions of engineering (9)
Part III	Metacognition	Knowledge (12)
		Regulation (13)
Part IV	Self-efficacy	Problem solving self-efficacy (14)

Factor Analysis

Exploratory factor analyses (EFA) were calculated for each part of the survey using the survey responses received at the beginning of the Fall 2013 semester (n=1094) to assess the construct validity of each part of the survey. Scree plots and the literature on each framework were used to determine the number of factors to test during the analysis. Items that loaded below 0.4 were removed from the analysis.[36] A list-wise deletion was used to account for missing data. This analysis was run in R using the nFactor package with a promax rotation as it allows for correlation between variables.[37]

Confirmatory factor analyses (CFA) were utilized for each part of the survey that loaded during the original EFA using the survey responses received at the end of the Fall 2013 semester (n=880) to confirm that the hypothesized model for each part of the survey provides a good fit to the data. This analysis was run in R using the laavan package for structural equation modeling.[38] Missing data for both EFA and CFA was handled by performing list-wise deletions.

General Linear Models

General linear models with each factor from the factor analysis as the dependent variable were used to examine differences among section types for the beginning of the semester responses (n=1094), end of the semester responses (n=880), and changes in responses from the beginning to the end of the semester (n=640). When significant differences existed among the section types, pairwise comparisons between the section types were considered using t-tests with pooled standard deviation estimates. Prior to building the models, chi-square analysis was used to determine if demographics and gender were independent of section type (HC, SEC, and no LC). Gender along with its interaction with section type were included in each analysis.

Results and Discussion

Survey Validation

Exploratory factor analysis (EFA) was used to validate the survey items' measurement of their intended constructs. Parts I, II, and III of the survey factored according to literature into the constructs displayed above in Table 1 using the survey responses collected at the beginning of the semester. The EFAs for Parts I (Goal Orientation), II (Expectancy x Value and Future Time Perspective), and III (Metacognition) of the survey were used to inform "measurement models" that were examined with confirmatory factor analyses (CFAs) conducted with the survey responses collected at the end of the semester. The CFA analyses reported in Tables 2-4 suggest that the measurement model fits the data with some limitations.

The chi-square statistic for Part I of the survey is 3778.332, making it significant. The degrees of freedom reported are 55. With CFA, the chi-square test indicates the difference between the observed and expected covariance matrices. Chi-square statistics close to zero with p-values greater than 0.05 indicate that there is statistically no difference between these matrices, indicating a good fit. The large chi-square value in this model is likely due to the large sample size. The chi-square statistic is often considered to be problematic because it is sensitive to sample size as it can be artificially inflated and significant without indicating a poorly fitting model with large sample sizes [39,40]. Another measure of fit in CFA is the Root Mean Square Error of Approximation (RMSEA), which is related to the residuals in the model. Values for RMSEA range from zero to one, with smaller values indicating a better model fit. Acceptable model fit is indicated by a value of 0.1 [39] or less and a good model fit is indicated by a value of 0.08 or less [41]. The RMSEA is 0.086 for this model indicating an acceptable fit. Another fit statistic to consider is the Comparative Fit Index (CFI) which assesses the improvement of the proposed model compared to an independence model where the observed variables are uncorrelated [42]. CFI values range from zero to one, with larger values indicating a better fit; acceptable model fit is indicated by a value of 0.9 [39,43]. The CFI for this model is 0.930 indicating an acceptable fit.

The chi-square statistic for Part II of the survey is 8858.887 with 136 degrees of freedom and is significant. As with Part I of the survey, this large chi-square value is likely due to the large sample size [39]. The RMSEA and CFI are 0.096 and 0.894 respectively indicating that the fit is borderline acceptable as the RMSEA is below 0.1 but the CFI is not above 0.90.

The chi-square statistic for Part III of the survey is 7412.098 with 190 degrees of freedom and is significant, again, likely due to the large sample size. The RMSEA and CFI are 0.070 and 0.902 respectively. These fit parameters suggest that the model is acceptable as these parameter values are within the acceptable fit range.

The fit parameters for the CFAs of each part of the survey are borderline acceptable. The acceptable fit rather than good fit may be explained in part by using the beginning of the semester surveys to determine the factors (EFA) and end of the semester surveys to confirm the model (CFA). Over the semester the students' attitudes and perceptions of engineering and their engineering problem solving practices may have become less inconsistent as they gained more experience in their engineering course. Additionally, the loss of those students who withdrew from the introductory course may be enough to shift the overall pattern of responses, thus making the CFA population slightly different from the EFA population.

Table 2: Confirmatory Factor Analysis (CFA) Estimates for Part I (Goal Orientation) of the Survey

To summarize acceptable values: Item reliability (R^2)≥ 0.50, Construct Reliability ≥ 0.70, and Average Variance Extracted ≥ 0.50.

Construct	Item	Standardized Factor Loadings	Standard Error	Item Reliability (R^2)	Construct Reliability	Average Variance Extracted
Performance Approach	Remembering enough from this class to impress other people.	0.526	0.041	0.277	0.727	0.476
	Doing better than the other students in this class on tests and assignments.	0.661	0.038	0.437		
	Impressing the instructor with your performance.	0.733	0.037	0.537		
	Getting the highest grade in this class.	0.421	0.046	0.177		
	Proving to other people that you are a good student.	0.59	0.038	0.348		
Mastery	Knowing more than you did previously about these course topics.	0.733	0.024	0.537	0.833	0.679
	Really understanding this course's material.	0.863	0.022	0.745		
	Feeling satisfied that you got what you wanted from this course.	0.772	0.026	0.596		
Work Avoid	Getting a passing grade with as little studying as possible.	0.842	0.033	0.709	0.890	0.759
	Getting through the course with the least amount of time and effort.	0.956	0.03	0.914		
	Not having to work too hard in this class.	0.754	0.03	0.569		

Table 3: Confirmatory Factor Analysis (CFA) Estimates for Part II (Future Time Perspective and Expectancy) of the Survey

To summarize acceptable values: Item reliability (R^2)≥ 0.50, Construct Reliability ≥ 0.70, and Average Variance Extracted ≥ 0.50.

Construct	Item	Standardized Factor Loadings	Standard Error	Item Reliability (R^2)	Construct Reliability	Average Variance Extracted
Expectancy	I expect to do well in this engineering course.	0.754	0.024	0.569	0.908	0.649
	I am confident I can do an excellent job on the assignments and tests in this engineering course.	0.829	0.025	0.687		
	Considering the difficulty of this engineering course, the teacher, and my skills, I think I will do well in this engineering course.	0.826	0.023	0.682		
	I am certain I can master the skills being taught in this engineering course.	0.777	0.022	0.604		
	I am certain I can understand the most difficult mterial presented in the readings for this engineering course.	0.689	0.028	0.475		
	I am confident I can undersand the most complex material presented by the instructor in this engineering course.	0.696	0.028	0.484		
	I believe I will receive an excellent grade in this engineering course.	0.777	0.03	0.604		
Present	What I learn in my engineering course will be important for my future occupatio	0.794	0.028	0.630	0.749	0.549
	I will use the information I learn in my engineering course in other classes I will t	0.804	0.025	0.646		
	My course work is preparing me for my first job.	0.73	0.032	0.533		
	I will not use what I learn in this engineering course.	-0.705	0.031	0.497		
	I will use the information I learn in this engineering course in the future.	0.826	0.025	0.682		
Future	I am confident about my choice of major.	0.752	0.031	0.566	0.722	0.526
	My interest in engineering outweighs any disadvantages I can think of.	0.804	0.028	0.646		
	I am considering switching majors.	-0.728	0.036	0.530		
	I want to be an engineer.	0.84	0.029	0.706		
	Engineering is the most rewarding future career I can imagine.	0.669	0.035	0.448		

Table 4: Confirmatory Factor Analysis (CFA) Estimates for Part III (Metacognition) of the Survey

To summarize acceptable values: Item reliability (R^2)≥ 0.50, Construct Reliability ≥ 0.70, and Average Variance Extracted ≥ 0.50.

Construct	Item	Standardized Factor Loadings	Standard Error	Item Reliability (R^2)	Construct Reliability	Average Variance Extracted
Regulation	I set a goal before solving the problem.	0.613	0.032	0.376	0.887	0.526
	I ask myself how well I have solved the problem once I have finished.	0.637	0.03	0.406		
	I ask myself if I have considered all options when solving the problem.	0.695	0.026	0.483		
	I ask myself now and then if I am meeting my goal.	0.709	0.029	0.503		
	I ask myself about the case before starting to solve the problem.	0.692	0.027	0.479		
	I summarize what I have learned after solving the problem.	0.614	0.034	0.377		
	I ask myself if I have considered all options after I solve the problem.	0.702	0.028	0.493		
	I ask myself whether I have considered my process carefully before I make a choice.	0.725	0.026	0.526		
	I find myself pausing regularly to check my understanding.	0.458	0.032	0.210		
	I consider several ways to solve the problem before I answer.	0.667	0.028	0.445		
	After I have solved a problem, I ask myself whether there is an easier way to solve it.	0.563	0.032	0.317		
Knowledge	I think I know whether I have understood the problem well.	0.643	0.023	0.413	0.877	0.400
	I know what kind of information is most important.	0.649	0.022	0.421		
	I think I am good at sorting out the information presented in the problem.	0.653	0.023	0.426		
	I can make myself solve the problem when I need to.	0.67	0.024	0.449		
	I find myself using helpful methods naturally when I solve the problem.	0.738	0.023	0.545		
	I know how well I did after solving the problem.	0.585	0.028	0.342		
	I am aware of the plans I use when solving the problem.	0.695	0.025	0.483		
	I try to think in the ways that have worked in the past.	0.641	0.023	0.411		
	I use different plans to solve the problem depending on the situation.	0.699	0.024	0.489		

Part IV of the survey, which included items on problem solving self-efficacy, did not hold as a factor with all of the items factoring below the cutoff of 0.4. As a result, this part of the survey was not used in subsequent CFA or regression analyses. It is likely that these items did not hold as a factor because at the time of the survey the students had only been in engineering for approximately two weeks, making it difficult for them to assess their confidence in solving an engineering problem. As such, an exploratory factor analysis (EFA) was conducted on Part IV using the survey responses collected at the end of the semester (n=880) since at this time the students had more experience with solving engineering problems making them more likely to assess their confidence in performing specific tasks. Using the end of the semester survey responses, Part IV of the survey held as one factor, as expected.[44] The factor loadings of specific items from Part IV of the survey are in Table 5 below.

Table 5: Exploratory Factor Analysis Estimates for Part IV (Problem Solving Self-Efficacy)

Item	**Factor Loading**
Determine what may be wrong with a problem's solution if the answer seems unreasonable.	0.68
Check my work for errors.	0.63
Determine which approach is more reasonable, if two appraoches to solve an engineering problem gave different answers.	0.67
Identify the engineering principles in the problem before looking for corresponding equations.	0.79
Solve challenging engineering problems.	0.66
Draw pictures and/or diagrams to represent the situations described in engineering problems.	0.68
Learn from the problem's solution after I solve each engineering homework problem.	0.66
Solve an engineering problem symbolically before plugging in the numbers.	0.81
Use different approaches to solve an engineering problem when one does not work.	0.4

Comparison of Motivation and Metacognition Factors by Course Section Type

Using the factors presented in this paper, general linear models were used to explore differences between HC, SEC, and non-LC sections of a FYE course. For this work, we considered three datasets. Dataset 1 included survey responses from students collected at the beginning of the semester (n=1094) and was used to characterize initial differences between the three types of sections. Dataset 2 was made up of survey responses collected from students at the end of the semester (n=880) and was used to examine the differences between the section types at the end of the course. Dataset 3 included the change for each survey item for students who completed both administrations of the survey (n=640) and was used to examine changes that occurred over the course of the semester.

<u>Dataset 1: Beginning of the semester responses</u>

General linear models were used to determine if certain motivation and metacognition profiles were evident in students enrolled in HC, SEC, or non-LC sections of the course at the beginning of the semester. Pearson's Chi-squared test was used to determine if race and gender were associated with section type. Gender was found to be associated with section type (p-value=0.00098 and race was found not to be associated with (p-value=0.3047). As such, gender and its interaction with section type were included in each model. The results of these analyses are displayed in Table 6.

Table 6: Beginning of the semester, general linear model analyses results and follow-up pairwise comparisons using t-tests with pooled standard deviation estimates results. Section type means within a row with different letters significantly differ ($\alpha = 0.05$). Overall F test significant (· , *, **) for section type at an alpha of 0.1, 0.05, and 0.001, respectively.

	Mean ± Standard Deviation		
	HC	**SEC**	**Non-LC**
Expectancy*	4.158 ± 0.662^{a}	3.989 ± 0.681^{b}	3.983 ± 0.675^{b}
Future* **	3.374 ± 0.521^{a}	3.567 ± 0.506^{b}	3.593 ± 0.499^{b}
Mastery ·	4.744 ± 0.485^{a}	4.529 ± 0.710^{b}	4.627 ± 0.626^{ab}
Knowledge ·	4.069 ± 0.380^{a}	3.935 ± 0.535^{b}	3.985 ± 0.488^{ab}

For students enrolled in the HC sections, there were higher reported levels of expectancies compared to students in the SEC and non-LC sections at the beginning of the semester. Additionally, students in the HC sections had higher perceptions of their knowledge of cognition and higher mastery orientation compared to students in the SEC sections. Students enrolled in the HC sections had lower reported levels of future perceptions than students enrolled in the SEC and non-LC sections (Table 6). Students whose academic performance is traditionally high often expect to maintain these high grades; this is reflected by the HC section having higher reported expectancies. As the HC is restricted to students with superior academic achievement and their mission is focused on developing students who are life-long learners, it seems reasonable that students with higher levels of mastery goal orientation would be attracted to the HC. The knowledge of cognition construct includes processes that facilitate the reflective aspect of metacognition. This suggests that students who feel that they know when, why, and/or how to use metacognitive strategies when solving an engineering problem may choose to join and participate in the HC in hopes of gaining more from the HC section than a non-LC section of the course. Lower ratings of future perceptions of engineering are difficult to explain through quantitative methods. It is possible that these students have broader future goals where becoming an engineer is simply a stepping stone to their future career, such as studying biomedical engineering before continuing to medical school to become a doctor. Alternately, students may be studying engineering for reasons other than their positive perceptions of the field such as others pushing them toward engineering based on their high academic achievement in high school. Finally, as students enter an engineering program they often have a limited understanding of what it means to be an engineer, and have yet to develop engineering related future goals.

SEC sections reported higher future perceptions of engineering, lower perceptions of knowledge of cognition, lower mastery orientation, and lower expectancies compared to students in the HC section at the beginning of the semester. Like students in the SEC sections of the course, students in the non-LC sections had higher future perceptions of engineering and lower expectancies than students in the HC section. No significant differences were observed between students in the SEC and non-LC sections. High future and low expectancies reflect students' strong desires to be engineers despite having some insecurity about their ability to solve engineering problems. Based on the results from the beginning of the semester survey responses there are no clear motivational or metacognitive differences between students in the SEC and non-LC sections of the course, despite the mission of the SEC, which is to prepare students for engineering courses and provide students with extra resources.

Dataset 2: End of the semester responses

General linear models were used to characterize differences in certain motivation factors of students in HC, SEC, or non-LC sections of the course at the end of the semester. Pearson's Chi-squared test was repeated, due to a differing population, to determine if demographics and gender were associated with section type. Gender was found to be associated (p-value=0.000873) and demographics were found not to be associated with section type (p-value=0.184). As such, gender and its interaction with section type were included in each model. The results of these analyses are displayed in Table 7.

Table 7: End of the semester, general linear model analyses results and follow-up pairwise comparisons using t-tests with pooled standard deviation estimates results. Section type means within a row with different letters significantly differ ($\alpha = 0.05$). Overall F test significant (*, **) for section type at an alpha of 0.05 and 0.001, respectively.

	Mean ± Standard Deviation		
	HC	**SEC**	**Non-LC**
Expectancy*	3.966 ± 0.527^{ab}	4.066 ± 0.531^{a}	3.920 ± 0.533^{b}
Future**	3.408 ± 0.556^{a}	3.618 ± 0.487^{b}	3.550 ± 0.564^{b}
Performance*	3.195 ± 0.800^{a}	3.453 ± 0.688^{b}	3.351 ± 0.744^{b}

At the end of the semester, students in the HC section had significantly lower future perceptions of engineering and performance goal orientation than students in the other two sections (Table 7). This may indicate that students who completed the survey at the end of the semester in the SEC and non-LC sections have a higher drive for grade based performance than the students in the HC section of the course. The lower perceptions of the future for HC sections are consistent with what was seen at the beginning of the semester. At the end of the semester, students in the SEC had higher expectancies of success than students in the non-LC sections. This suggests that at the end of the term the students in the SEC sections are more confident in their abilities to succeed in their engineering course than the students in the non-LC sections.

The interaction between section type and gender was found to be significant in the overall model for future perceptions of engineering at the end of the semester. Significant differences in future perceptions of engineering were found between the females in the HC sections compared to females in the non-LC and SEC sections with p-values of 0.0052 and 0.0018, respectively. The mean future perception of engineering for women in HC, SEC, and non-LC sections are 3.204 ± 0.580, 3.574 ± 0.550, and 3.483 ± 0.622, respectively. This suggests that women in the HC sections are not seeing engineering as a possible future career as much as women in other sections. Some possible reasons to consider are that women in HC have other careers that they are considering and women in HC are not exposed to careers in engineering that they can identify with resulting in less positive future perceptions of engineering. No significant differences in future perceptions of engineering were observed between males in the three sections.

<u>Dataset 3: Changes in responses from beginning to end of the semester</u>

Since looking at the beginning and end of the semester responses only provides snapshots in time for the overall groups, an additional dataset was created that included changes in students responses for each item on the survey from beginning to end of the semester. Using this merged dataset, General linear models were used to investigate changes in motivation and metacognition profiles that were evident in students enrolled in HC, SEC, or non-LC sections of the course. Pearson's Chi-squared test was used to determine if race and gender were associated with section type. Gender was found to be associated with section type (p-value=0.0213) and race was found not to be associated with section type (p-value=0.197). As such, gender and its interaction with section type were included in each model. The results of these analyses are displayed in Table 8.

Table 8: Changes in responses from beginning to end of the semester general linear model analyses results and follow-up pairwise comparisons using t-tests with pooled standard deviation estimates. Section type means within a row with different letters significantly differ ($\alpha = 0.05$). Overall F test significant (˙) for section type at an alpha of 0.1.

	Mean ± Standard Deviation		
	HC	**SEC**	**Non-LC**
Expectancy ˙	-1.137 ± 2.653^{a}	-0.528 ± 2.216^{b}	-0.573 ± 2.275^{b}
Mastery ˙	-0.184 ± 0.794^{a}	0.0427 ± 0.722^{b}	-0.0995 ± 0.889^{ab}

Students in the HC sections of the course were found to have statistically significant changes in expectancy compared to students in the SEC and non-LC sections of the course. The expectancy of success for students in HC sections decreased more than that of students in the other sections (Table 8). This result mirrors previous work with engineering students indicating decreased expectancy over the course of a year.[8,45,46] Students may enter an engineering program with pre-existing ideas about their abilities and by the end of their first semester they are confronted with the reality that they may not be able to perform at that level in college courses. Additionally, students in the HC sections were found to have statistically significant changes in mastery goal orientation compared to students in the SEC sections. Mastery goal orientation slightly decreased over the course of the semester for students in HC sections, while slightly increasing for students in the SEC sections (Table 8). The change observed in HC students may indicated a shift from learning to performance as students neared final examinations, which account for a significant portion of their grade.

Conclusions

This study validated a survey instrument that measures students' affect toward engineering. It was utilized to measure the impact of living-learning communities on the motivation and perceived metacognitive strategies of first year engineering students during their first university engineering course. Distinct motivation profiles, groupings of significant motivation factors, emerged for HC, SEC, and non-LC student populations.

The HC seems to be attracting their targeted group of students, as students with higher mastery orientation and higher perceptions of their knowledge of cognition. Students in the SEC were not significantly different than those in the non-LC sections of the course at the beginning of the semester, but did have higher expectancies of success in their engineering course at the end of the semester. At the end of the semester, women in the HC sections of the course had significantly lower future perceptions of engineering than the women in the SEC and non-LC sections of the course. The expectancy of success for students in HC sections decreased more than that of students in the other sections. Additionally, mastery goal orientation slightly decreased over the course of the semester for students in HC sections, while slightly increasing for students in the SEC sections.

The students' level of perceived use of metacognitive practices remained unchanged throughout the semester. The LCs or the course as a whole may consider including pedagogical interventions that build metacognitive skills. No comparisons have yet to be made between courses based on variations in teaching methods.

Implications for Practice

This survey has potential benefits beyond research purposes. It can be a useful tool for instructors to learn more about their students by identifying the affective needs of his or her class. Professors could then address these needs by modifying their teaching style to appeal to the motivations of each population of students. Another potential use of the tool is as an evaluation tool to determine readiness for advanced programs such as early admittance, research groups, internships, or summer school. Further work would be required to establish the validity of this application of the survey and to establish admittance criteria.

Limitations and Future Work

One of the limitations of this work is that the interpretation of items has not been assessed so it is possible that students are misinterpreting items. As such, future work will include further validation and reliability testing of the survey to include test-retest and focus groups. During the focus groups, special attention will be paid to the items that have low item reliability, and to interpreting the meaning of the lower ratings of future perceptions of engineering for students in the HC. The CFA results report in this paper are borderline acceptable which could have been caused by the two samples (beginning of the semester and end of the semester survey responses) used to test the model being more unique than we expected. While the same students were used to determine and then test the model, they had been in a semester of engineering which likely altered their perceptions and motivations towards engineering. Future work will determine if two separate models are more appropriate with one representing the beginning of the semester and one the end of the semester. In the general linear model analysis, grade point average and course grade were not controlled for, both of which have been shown in other work to be connected to student motivation. In future work, these two variables will be controlled for to provide a more robust analysis of the data. Additionally, the stability of the survey items has not been assessed yet and may have an effect on the results from dataset 3 as the differences that were observed could have something to do with the stability of the items in those two factors. Future work will include assessing the stability of the survey items, so that the natural noise that occurs in responses can be appropriately taken into account. The work avoid construct is understudied in the field of engineering and requires further exploration to understand how a motivational construct with limited ties to social evaluation influences academic performance.

Acknowledgement

This study was funded through a grant from the National Science Foundation (award # EEC-1055950).

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