Factors Influencing Conceptual Understanding in a Signals and Systems Course

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Dr. Finelli’s current research interests include student resistance to active learning, faculty adoption of evidence-based teaching practices, and the use of technology and innovative pedagogies on student learning and success. She also led a project to develop a taxonomy for the field of engineering education research, and she was part of a team that studied ethical decision-making in engineering students.
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Abstract

Previous studies show that many engineering undergraduates lack conceptual understanding of signals and systems. Although there is evidence that teaching style impacts conceptual understanding, there are few studies that investigate other reasons that some students understand the concepts while others do not. This paper tests how well a subset of factors from the Model of Educational Productivity (student ability and motivation, instructional quality and quantity, and home, peer, and classroom environment) explain the variance in signals and systems conceptual understanding at the end of an introductory undergraduate course. We present results from a linear regression model on data collected from surveys and concept inventories \( n = 124 \) that show the hypothesized factors explained 28% of variance in post-test conceptual understanding. Further, two of the factors were significantly predictive of conceptual understanding: ability \( (p < 0.01) \) and motivation \( (p < 0.10) \).

1 Introduction

Signals and systems (SS) is a standard electrical engineering (EE) undergraduate course covering linear time-invariant (LTI) system properties, convolution and system responses, Fourier transforms (FT), Laplace transforms (LT), and filtering. These topics are fundamental to signal processing, image processing, and machine learning specializations, all of which are high-demand areas for graduates.

Despite the importance educators place on concepts in SS, studies show that students typically do not learn even half of new concepts in a SS course [1], and that students can derive the correct answer on procedural questions without being able to explain the underlying concepts [2], [3]. For example, students may be able to use convolution to derive the output of a LTI system given an input and impulse response, without understanding how the math fundamentally relies on the properties of LTI systems, which is one of the first major concepts in SS courses.

SS may be such a challenging course because it is mathematically advanced, theoretical, hard to relate to everyday experiences, and/or because it requires students to correctly categorize multiple topics (e.g., discrete vs. continuous and time vs. frequency) [4], [5]. Regardless of the reason, many students come to fear SS and it is considered a weed-out course at many universities [6]. Instructors have tried including more hands-on activities or using research-based instructional practices to help students learn and to decrease the fear surrounding SS, but conceptual understanding remains low [7].

Although there is evidence that active learning aids conceptual understanding [7], there are few previous studies that investigate other reasons that some students understand SS concepts. This
work investigates factors that correlate with student conceptual understanding at the end of a SS course. Our goal is to understand what factors students, instructors, and curriculum designers can control to increase student conceptual understanding. Our research question is: Which factors predict how many SS concepts students learn during an undergraduate SS course?

2 Background

2.1 Conceptual Understanding in SS

In [8], diSessa provides a historical overview of conceptual change research and acknowledges that there is still disagreement on what “conceptual understanding” (CU) means. However, there are a few common ways of characterizing CU, such as how it is often defined in contrast with procedural knowledge, e.g., [9], [10]. Roughly speaking, procedural knowledge is how to do something, whereas CU is knowing relations between pieces of information in a way that allows knowledge transfer to new contexts [9]. For example, Rittle-Johnson [11, p. 2] defines procedural knowledge as “the ability to execute action sequences to solve familiar problems” and conceptual understanding as “understanding principles governing a domain and the interrelations between units of knowledge in a domain.”

Researchers hypothesize a positive feedback loop between CU and procedural knowledge. Theorized benefits of increasing students’ CU include providing structure to help students recall and select the correct procedure, more easily transferring procedures to new contexts, and developing more expert-like knowledge structures [9], [12]. In turn, procedural knowledge can free cognitive resources to concentrate on understanding and can aid in representing complex concepts in more easily digestible ways [9]. Both types of understanding are necessary, but multiple large research studies have shown that students are not building conceptual understanding in their courses [1], [13].

Concept inventories are one common approach to measuring CU. These inventories are quantitative instruments that consist of collections of validated, standardized conceptual questions. Due to their multiple-choice nature, students may guess the correct answer to questions, leading to an inaccurate assessment their conceptual understanding [3]. However, concept inventories remain useful for testing a large number of students, comparing results across universities, and investigating how performance on the test correlates with other variables (e.g., grades or demographics) [10]. Following the seminal research with the Force Concept Inventory, researchers typically give concept inventories in a pre/post-test format and calculate normalized gain statistics, $\langle g \rangle = \frac{\text{post} - \text{pre}}{\text{max-pre}}$, to measure how many concepts students learn as a percentage of how many that they did not know at the time of the pre-test [13].

The Signals and Systems Concept Inventory (SSCI) has 25 multiple-choice questions on five topics: background mathematics, LTI, convolution, transform representations, and filtering [1]. For more granularity, we split the transform representations questions into FT and LT for a total of six topics. See Ref. [1] for a few example questions. This study uses the current revision (version 5) of the continuous time (CT) SSCI [1].

Because of the initial extensive study (involving 7 schools and over 900 students), the SSCI offers a benchmark for comparison across institutional contexts [1]. Wage, Buck, Wright, and Welch [1]
found the average (and standard deviation) SSCI gain was $\langle g \rangle = 0.20 \pm 0.07$ in lecture-based classrooms and $0.37 \pm 0.06$ in active learning classrooms. The low fraction of new concepts learned during students’ SS course is disappointing, though the results are encouraging for proponents of active learning.

2.2 Model of Educational Productivity

There are many frameworks that try to explain what factors help students learn; however, few look specifically at factors relating to CU. Therefore, this study uses an existing model for factors that influence procedural learning: the Model of Educational Productivity (MoEP) [14].

The MoEP is an empirically tested linear regression model to explain variation in learning. It has nine factors grouped into three categories: three student factors (age, ability, and motivation), two instructional factors (quality and quantity), and four environmental factors (exposure to mass media and home, peer group, and class environment). We test the original, single-level version of the model without mediating or moderating factors.

Walberg and his colleagues tested and developed the model for high school students, but it has also been applied at the undergraduate level [15]–[17]. For example, Bruinsma and Jansen [15] found that the MoEP (removing the mass media factor) transferred reasonably well to the higher education setting, explaining 23% of variance in grades among first-year students in a mathematics and natural sciences department.

Tab. 1 includes example previous measures for each factor. Note that some of the early studies used existing surveys and therefore had flawed measures, e.g., Walberg used SES as a “poor surrogate” for ability [18, p. 288]. Despite this poor measure, the authors still demonstrated the usefulness of the MoEP.

3 Methods

We use regression models to test for significant predictors of CU at the end of a SS course and to determine how much variance in CU the MoEP factors explain. We measured students CU using the SSCI and the MoEP factors using a short survey.

3.1 Data Sample

This study includes undergraduates at the University of Michigan (UM) who took the main undergraduate signals and systems course in Fall 2019 or Winter 2020. Most of the students were in their second or third year of undergraduate studies, but were classified as third or forth years in terms of the number of credits they have taken. The course emphasizes continuous time signal analysis and was taught using the free online textbook by Ulaby and Yagle [19]. In addition to the topics covered by the SSCI, the course briefly discusses sampling theory and the relationship between continuous and discrete time representations.

The course was lecture-based and accompanied by a required lab section that met five times for labs on impulse response, envelope detector, frequency modulation discriminator, amplitude modulation radio, and feedback control. Due to the covid-19 pandemic, the Winter 2020 section
moved to remote instruction half-way through the semester and students’ grades defaulted to pass/fail for all courses (students could elect to show a letter grade for the course, but we do not have data on how many of them chose to do so).

Students took the pre-test SSCI in-person during their assigned lab section in the second week of classes (in previous offerings, there was no scheduled lab meeting this week). Students took the post-test SSCI and an additional survey during their last class before finals as part of a review session in Fall 2019. In Winter 2020, students took an online version of the SSCI with answer options randomized in the last week of classes before finals preparation. Students received a small amount of course credit for completing the SSCI - they were not graded based on their score. There was no incentive for students to take the research survey in Fall 2019. Due to the grading changes, participating students in Winter 2020 had a chance to win a small gift card.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Previous definitions/measures</th>
<th>Our measures</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Student</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Often excluded when participants are similar ages [14], [20], [21]</td>
<td>Not included</td>
</tr>
<tr>
<td>Ability</td>
<td>Grades in prerequisite courses or prior GPA [15], [21]</td>
<td>SSCI pre-test score</td>
</tr>
<tr>
<td>Motivation</td>
<td>Participation in optional, course-related activities [14], [21]</td>
<td>If students want to graduate in EE</td>
</tr>
<tr>
<td></td>
<td>Expectancy-value theory (measures self-efficacy, interest, and positive feelings) [15]</td>
<td>If understanding convolution, LTI, FT, LT, and filtering will benefit their career</td>
</tr>
<tr>
<td><strong>Instructional</strong></td>
<td>Use of didactic or student-centered instruction methods [14], [18]</td>
<td>Students rate overall quality of instruction of SS</td>
</tr>
<tr>
<td>Quality</td>
<td>Quality of presentation, organization, assessment, and pace [15]</td>
<td></td>
</tr>
<tr>
<td>Quantity</td>
<td>Hours students spent on homework in a typical week (self-reported)</td>
<td>Avg. hours spent on SS homework Percentage of lectures attended</td>
</tr>
<tr>
<td>Classroom</td>
<td>Class morale [14], [20]</td>
<td>If the learning environment was comfortable</td>
</tr>
<tr>
<td></td>
<td>How students feel in class (curious, uncomfortable, stupid, confident, successful, unhappy)  [21]</td>
<td></td>
</tr>
<tr>
<td><strong>Environmental</strong></td>
<td>Highest educational status of parents/guardians [20], [21]</td>
<td>Highest education status of students’ parent(s)/guardian(s)</td>
</tr>
<tr>
<td>Home</td>
<td>If they had an encyclopedia or a newspaper in the home [14], [18]</td>
<td></td>
</tr>
<tr>
<td>Peer-group</td>
<td>If schooling and grades are important to friends [20], [22]</td>
<td>How often peers helped their understanding of SS</td>
</tr>
<tr>
<td>Mass media</td>
<td>Hours watching television [14]</td>
<td>Not included</td>
</tr>
</tbody>
</table>

Table 1: Example previous measures of the MoEP factors and summary of measures for this study. Surveys additionally asked students for their gender identity and which racial and ethnic group(s) they identify with.
Of the 134 enrolled students in Fall 2019, 118 took the pre-test and 91 took the post-test. A similar number of students took the pre-test in Winter 2020 (114 out of the 134 enrolled), but only 69 took the post-test. This study considers only the sub-sample of UM students in the SS course in Fall 2019 or Winter 2020 who took the SSCI at the start and end of their SS course, signed the consent form, and who responded to the survey questions ($n = 124$).

3.2 Survey for MoEP factors

Our dependent variable is students’ conceptual understanding at the end of the SS course, as measured by students’ raw post-test SSCI scores. Following the framework of the MoEP, we include student, instructional, and environmental independent variables. All questions are coded such that we predict a positive correlation coefficient between the factors and our outcome variables. All Likert style questions had 5-options and followed the design principles suggested by [23]. Tab. 1 summarizes the measures used.

We do not include the age variable. We use students’ scores on the pre-test to measure ability. Our measure of motivation most closely matches the expectancy-value theory used by [15]; we use the data from seven Likert style survey questions to capture students interest in and perceived value in learning EE. The questions asked how likely students are to major in EE, if learning SS is interesting, and if students think learning the different SS topics will benefit their career.

For both instructional variables, we use subjective student opinions rather than a measure of the teaching style or amount of homework assigned; our commentary is not meant to reflect on the quality of the given instructor. For the instructional quality variable, we use responses to a Likert style question that asked students to rate the overall quality of instruction in SS. For instructional quantity, we asked students to self-report the average numbers of hours they spent on homework each week and what percentage of lectures they attended. In Fall 2019, our survey questions were ambiguous, and some students counted time spent on pre-/post-labs toward homework time while others did not. Likewise, students who watched lectures online may or may not have included that in their attendance responses. We clarified the language for these questions in Winter 2020 to specifically ask students to include time spent on pre-/post-labs toward their homework time and online lectures toward their attendance.

We use the highest educational status of students’ parents/guardians to measure home environment. Following [15], we do not include the mass media variable. Like our measure of instructional quality, we took a direct approach and asked students if the SS course learning environment was comfortable. Finally, we included a Likert style question on if peers helped students’ understanding of SS material to measure peer environment.

3.3 Model testing

The main contribution of this study is testing the MoEP as a model for students’ SS conceptual understanding. Our outcome variable is conceptual understanding at the end of SS and our key independent variables are ability, motivation, instructional quality, instructional quantity, home environment, classroom environment, and peer-group environment.

We compare the results to a model that includes race/ethnicity, gender, and SS semester as control
variables. Ref. [14] found adding race/ethnicity and gender increased the variance explained from 25% to 34-36%. The authors hypothesize that the increase stems from the control variables serving as proxies for poorly measured factors and that adding the controls would be insignificant if the factors were measured accurately. The semester variable in our study could similarly capture differences in instruction or class environment that our survey does not fully measure.

3.4 Data Limitations

We face a number of data limitations in this study. First and foremost is that our data set is relatively small and homogeneous; all of the participants took one of two signals and systems classes. The small sample size means our statistical tests have low power, so we can expect few of the coefficients in our regressions models to reach statistical significance. The homogeneity of our sample population means there is little variance in some of the independent variables, further decreasing the likelihood that they will be significant.

The next problem is the definition of our variables. Some variables are defined differently than what is common in the literature (e.g., peer environment). Further, we only had a short survey, so the quality of instruction, peer environment, home environment, and class environment variables are measured by a single question rather than a multiple-question Likert scale. In our regression, we treat home environment as a categorical (discrete) variable, but we treat the other variables as continuous measures. The underlying assumption is that student responses capture a discretized measure of the underlying construct and that the spacing between items is roughly equal. In a follow-on study, some of our participants will take a longer survey with additional items to reduce the impact of this limitation; however, we do not yet have this data.

Finally, the impact of covid-19, and particularly the unexpected shift to online instruction, impacts the Winter 2020 data. We discuss how the semester students took SS is correlated with many other variables further in the results section.

4 Results

We first briefly present the raw SSCI statistics. For the SS classes at the UM in Fall 2019 and Winter 2020, and considering only the \( n = 124 \) students in our sample, the average class SSCI pre-test scores was 49.5\% \pm 12.0\%, the post-test score average was 73.4\% \pm 14.4\%, and the

![Figure 1: Histogram of student scores on the pre-test and post-test SSCI.](image)
average student gain was 47.8% ± 27.3%. Fig. 1 shows a histogram of student scores out of a maximum possible score of 25. Average student scores improved for all SSCI sub-tests.

Before presenting the main linear regression results, the next sections provide a more complete overview of our data.

4.1 Independent variables: Descriptive statistics

Our two student independent variables were ability and motivation. We used the pre-test score to measure ability and seven survey questions to measure motivation. Looking at the distribution of the responses in Tab. 2, we note that most students were interested in learning SS, even though many did not expect to graduate with a EE degree (many computer engineering majors at UM elect to take SS from a list of possible core elective requirements). Students thought convolution was the topic least likely to benefit them in their careers, while they thought filtering was the most likely to be beneficial (only one person disagreed that it would benefit them).

The responses to the instructional quantity questions were diverse. Students reported spending 1.5 to 48 hours on homework per week (average 8.4 hours, standard deviation 5.7 hours) and attendance ranged from 0 to 100% (average 70%, standard deviation 33.8%).

For instructional quality, 85% of students thought that the instruction was either good or excellent; no students thought it was poor. Likewise, most (69%) students agreed that the classroom environment made them feel comfortable, with 11% disagreeing and the remaining 20% responding neutrally. The responses to how much peers helped their understanding were more spread out; 29% of students responding neutrally, 32% thought peers helped only a little or not at all, and 39% thought peers helped a lot or a great deal. Finally, for the home environment variable, roughly an equal number of students (26-33%) said the highest education status of their parent(s)/guardian(s) was a bachelor’s degree, a master’s degree, or a professional degree.

For the demographic variables, 100 students were male and 24 were female. To protect student anonymity, we defined a categorical race variable that divided students into white (n = 71), Asian (n = 34), and other (n = 19) as the possible races. The other category included all students that responded that they were another race or biracial.

<table>
<thead>
<tr>
<th></th>
<th>SD</th>
<th>D</th>
<th>N</th>
<th>A</th>
<th>SA</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plan to graduate in EE</td>
<td>19</td>
<td>26</td>
<td>10</td>
<td>15</td>
<td>54</td>
<td>3.48</td>
</tr>
<tr>
<td>SS is interesting</td>
<td>2</td>
<td>9</td>
<td>14</td>
<td>63</td>
<td>36</td>
<td>3.98</td>
</tr>
<tr>
<td>Beneficial to career: Convolution</td>
<td>7</td>
<td>23</td>
<td>34</td>
<td>42</td>
<td>18</td>
<td>3.33</td>
</tr>
<tr>
<td>Beneficial to career: LTI</td>
<td>3</td>
<td>12</td>
<td>25</td>
<td>61</td>
<td>23</td>
<td>3.71</td>
</tr>
<tr>
<td>Beneficial to career: FT</td>
<td>2</td>
<td>8</td>
<td>16</td>
<td>54</td>
<td>44</td>
<td>4.05</td>
</tr>
<tr>
<td>Beneficial to career: LT</td>
<td>2</td>
<td>5</td>
<td>15</td>
<td>59</td>
<td>43</td>
<td>4.10</td>
</tr>
<tr>
<td>Beneficial to career: Filtering</td>
<td>0</td>
<td>1</td>
<td>7</td>
<td>41</td>
<td>75</td>
<td>4.53</td>
</tr>
</tbody>
</table>

Table 2: Summary of responses to motivation questions asking students if they plan to graduate in EE, think SS is interesting, and if they think understanding each of the SS topics will be beneficial in their career. Likert response options are strongly disagree (SD), disagree (D), neither agree nor disagree (N), agree (A), and strong agree (SA). The reported mean is calculated by numbering the responses from 1 to 5.
4.2 Motivation variable

We next consider if the seven survey questions relating to motivation can be combined to form a composite variable. To do so, we used the principal component factor analysis method [24]. Since all the questions were on a five-point Likert scale, we used the raw data directly.

The Kaiser-Meyer-Olkin (KMO) measure indicates if a factor analysis is warranted. A KMO close to 1 suggests the variables are linearly dependent and all measure the same underlying construct, while a value below 0.5 or 0.6 is usually considered unacceptable [25]. The KMO for the seven motivation survey questions was 0.84, suggesting that the items merited a factor analysis. There was only a single eigenvalue greater than one, suggesting a single variable, which we call motivation. Cohen’s alpha was 0.84 (there was a 0.47 average covariance with seven items in the scale). We formed the motivation variable as the average of the seven items. The final motivation variable has a mean of 3.9, a standard deviation of 0.75, and a range of 1.4-5.0.

4.3 Simple Correlations

Having considered descriptive statistics for all the variables separately, this section now presents correlations between the independent variables. Ideally, the independent variables would be uncorrelated, suggesting that they measure different underlying constructs.

Tab. 3 shows the significant ($p<0.10$) pair-wise correlations between the independent variables. The two highest correlations are between motivation and instructional quality (0.45) and between instructional quality and classroom environment (0.50). The relation between quality and classroom environment is easy to imagine: students who feel comfortable or uncomfortable with the learning environment are be likely to attribute art of that to the instructor. The relation between motivation and instructional quality can be similarly explained by the instructors impact on students, e.g., a good instructor may help students see the value in the class material.

Tab. 3 shows that the semester variable is significantly correlated with most of the other variables. We hypothesize that the students in the Fall 2019 and Winter 2020 were very similar coming into

<table>
<thead>
<tr>
<th>Factor</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4a)</th>
<th>(4b)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Ability</td>
<td>1</td>
<td></td>
<td>-0.26</td>
<td>0.20</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) Motivation</td>
<td>.</td>
<td>1</td>
<td>0.45</td>
<td>0.26</td>
<td>0.28</td>
<td>0.26</td>
<td>0.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) Quality</td>
<td>.</td>
<td>-0.20</td>
<td>0.18</td>
<td>0.50</td>
<td>0.27</td>
<td>-0.27</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4a) Quant: homework</td>
<td>.</td>
<td>.</td>
<td>1</td>
<td>0.21</td>
<td>-0.20</td>
<td>0.42</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4b) Quant: attendance</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>1</td>
<td>0.18</td>
<td>0.28</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) Home env.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>1</td>
<td></td>
<td>0.20</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6) Classroom env.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>1</td>
<td>0.28</td>
<td>-0.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(7) Peer group</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(8) Semester</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Significant ($p<0.10$) pair-wise correlations between independent variables in the MoEP [14] (non-significant correlations are not listed). Bold numbers denote variables that are significantly correlated with $p<0.01$. For correlations between two continuous variables (ability and instructional quantity), we report standard correlation coefficients. For correlations involving one or two discrete variables (instructional quality and the three environmental variables), we report Spearman correlations.
SS (supported by the statistically insignificant correlation between semester and the pre-test ability measure). However, because of the interruption in instruction and switch to pass/fail grading due to covid-19, the population of students who chose to take the post-test in Fall 2019 is likely different. Covid-19 likely also explains the lower ratings of instructional quality and classroom environment for Winter 2020. Although there was a different instructor, both instructors historically have received high ratings and we do not believe there was such a significant difference in their teaching ability. Further, three students commented in the survey’s free response field that the unplanned for switch to online instruction impacted their perception of the class and made it harder to learn.

4.4 Regression Models

We now present our main results from the linear regression to test which factors from the MoEP predict CU. Our first regression model included the seven independent variables from the MoEP. All of the independent variables, except home environment, were continuous regressors. The second model additionally included the categorical race/ethnicity, gender, and semester control variables. Both models used robust statistics to correct standard errors for possible heteroskedastic noise. Tab. 4 summarizes the models.

The model without any control variables (see the middle column of Tab. 4) explains 27.8% of the variance in post-test SSCI score and is significant at the $\alpha = 0.01$ level. Ability ($\beta = 0.53, t(\text{df}=112) = 5.04, p<0.01$) and motivation ($\beta = 0.86, t(\text{df}=112) = 1.90, p=0.06$) are the only two statistically significant predictors, both with the expected positive coefficients. The coefficients of the several other independent variables are negative, but none are significant. None of the control variables are significant ($p>0.20$).

When we include the control variables (see the rightmost column of Tab. 4), the expanded model explains 30.4% of the variance. However, $R^2$ will always increase when we add variables to a linear regression model. The adjusted $R^2$ value takes into account that adding more variables will always increase the amount of variance explained; this measure only increases if the added variables explain more variance than is expected by chance. The adjusted $R^2$ value actually decreases slightly when we add the control variables as seen in the last row of Tab. 4, suggesting that these variables are not worth including.

After finding that ability and motivation were significant predictors, we tested if either was moderated by any of the control variables, or if either ability or motivation had a quadratic effect. We found no evidence of the control variables moderating the impact of ability or motivation nor of a quadratic effect.

For comparison, we ran a final regression model with only the two significant independent variables, ability and motivation, as the independent variables. The model (at $p < 0.01$) and both variables (at $p < 0.01$ and $p < 0.05$ respectively) were all statistically significant. This model explained 25.7% of the variance in post-test SSCI scores and had an $R^2$ value of 24.5%.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Without control variables</th>
<th>With control variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ability</td>
<td>0.53 (0.01)</td>
<td>0.51 (0.01)</td>
</tr>
<tr>
<td>Motivation</td>
<td>0.86 (0.06)</td>
<td>0.87 (0.08)</td>
</tr>
<tr>
<td>Quality</td>
<td>0.06 (0.91)</td>
<td>0.09 (0.85)</td>
</tr>
<tr>
<td>Quantity (homework)</td>
<td>0.02 (0.66)</td>
<td>0.02 (0.70)</td>
</tr>
<tr>
<td>Quantity (attendance)</td>
<td>0.00 (0.84)</td>
<td>0.00 (0.85)</td>
</tr>
<tr>
<td>Peer env.</td>
<td>−0.39 (0.20)</td>
<td>−0.35 (0.26)</td>
</tr>
<tr>
<td>Class env.</td>
<td>0.45 (0.22)</td>
<td>0.55 (0.16)</td>
</tr>
<tr>
<td><strong>R²</strong></td>
<td><strong>27.8%</strong></td>
<td><strong>30.4%</strong></td>
</tr>
<tr>
<td><strong>Adjusted R²</strong></td>
<td><strong>21.3%</strong></td>
<td><strong>20.8%</strong></td>
</tr>
</tbody>
</table>

Table 4: Coefficients (with p-values) and R² values for the regression models. The only categorical variable, home environment, is not included in the table as it was not significant. All of the models shown are for the raw post-test score as the output (on a scale of 0-25) and are significant at the $\alpha < 0.01$ level.

## 5 Discussion

This study addressed our research question: “Which factors predict how many SS concepts students learn during an undergraduate SS course?” In addition to considering significant factors in our regression results, the following sections also discuss the overall explanatory power of the linear regression model and the descriptive statistics on the SSCI scores.

### 5.1 Factors influencing understanding

The regression results allow us to test the predictive power of each independent variable, while controlling for the other independent variables. Our regression results (Tab. 4) show that only motivation and ability were significant when we controlled for all the variables. Further, when we ran a regression model with only these two variables, we found they were able to explain 25.7% of the variance in post-test scores. This suggests one could predict outcomes in SS conceptual understanding based only on measurements of ability and motivation almost as well as basing a prediction on all variables in the MoEP. However, the finding that these variables remain significant in the full model is arguably more important because it suggests that ability and motivation are significant even when we control for the other variables in the MoEP.

There are two likely explanations for why only two of the predicted seven independent variables were significant. First, as discussed in our methodology section, our survey instrument is incomplete and contains some measurement error. Second, our sample population is students from UM who had one of two instructors, similar homework assignments, and similar lecture material (though students were split into two sections in both semesters). Although we explicitly measure student perception rather than directly measuring the environment, there is still very little variance in the instructional variables and the classroom environment variable, excluding the influence of covid-19 and the switch to online learning in Winter 2020. These instructional and environmental independent variables might become significant if we were to survey students across multiple courses at different universities.
5.2 Explanatory power of regression models

The regression models with the seven independent variables explained 28-30% of the variance in post-test score, depending on whether we included the demographics and semester control variables. This is less than the amount explained in the early studies with high school students [22], but more than the amount explained in the original tests of the MoEP [14] and in the tests in other university settings [15].

As the MoEP was originally tested for measuring learning in high school students, we consider the 28% of variance in conceptual understanding among undergraduate students to be high. Adding variables specific to undergraduate students would likely help explain more of the variance. Similar to the claim in [14], we also expect designing additional survey questions to better measure the seven factors would increase the explanatory power of the model.

Walberg [14] suggests that race and gender variables should not increase the explanatory power of the MoEP if the environmental variables are properly measured. We see only a small increase in explanatory power when including gender, race, and semester, and none of these variables are significant. Further, the $R^2$ value of the model decreased when we added the control variables, suggesting that including them is not useful. Because our environmental variables are not significant, it is difficult to say if the changes in the coefficients between models with and without demographics reflect poorly measured environmental variables.

5.3 Conceptual understanding

Although it is not the main focus of this study, by collecting pre-post SSCI data, we were also able to compare CU gain to other studies. We note that our observed gain is larger than the 20-37% gains reported in [1]. Other studies report similar [26] or much larger [27] gains (70% or more), but these are in upper-level digital signal processing courses.

One hypothesised reason for the high pre-test scores and gain is the effect of prerequisites, and specifically differential equations at UM. Like at many institutions, differential equations can be either a prerequisite or a co-requisite with SS, but 67% of UM students take it as a pre-requisite. This mathematical background, particularly being introduced to convolution, perhaps helped students in SS.

As a specific example of how a prerequisite could increase both the pre-test score and gain, we hypothesize that students may understand convolution at the beginning of the semester, thus raising their pre-test scores, but not yet know it is the correct operation to use to compute the output of a LTI system given the input and impulse response. As evidence that students have some background on convolution, 66% of students correctly answered question 14 on the pre-test, which tests whether students understand the commutative property of convolution. As corresponding evidence that students do not fully understand how to apply convolution to LTI systems, students scored 30-35% on the two convolution questions (13 and 15) that require recognizing the output of an LTI system given plots of the input and the impulse response. Since students understand much of what is needed to answer questions 13 and 15, it is easier for them to gain the conceptual understanding by filling in a small gap in their knowledge. This study did not gather data to test the proposed hypothesis, so we leave this as a direction for future work.
6 Conclusion

We used the Model of Educational Productivity as a basis for collecting survey data on seven possible factors: student motivation, student ability, instructional quality, instructional quantity, home environment, peer group environment, and classroom environment. We excluded two variables from the original MoEP, student age and mass media, based on our sample population of undergraduate students.

The regressions with the MoEP factors explained 28-30% of variance in conceptual understanding at the end of SS. We conclude that the model is a good starting place for understanding conceptual understanding in an undergraduate setting. However, the model could be improved by tailoring factors to undergraduate students. For example, course selection might have a significant influence for college students since they generally have some freedom in their curriculum. We recommend future studies test other models of learning to see if a different model may more successfully explain differences in conceptual understanding.

We found two of the factors, ability and motivation, were significant across models, even when controlling for all other factors and demographic variables. Future work should investigate if the relationship is causal (higher levels of ability and motivation lead to more conceptual understanding) or if it is mediated by another variable. If the relationship is found to be causal, instructors can use this finding to focus more attention on enforcing prerequisites or providing materials for students without sufficient background knowledge. Instructors can also motivate students with real-world applications and examples of how signals and systems concepts may be useful to students in their future classes or careers.

7 Acknowledgements

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References


