The CLICK Approach and its Impact on Learning Introductory Probability Concepts in an Industrial Engineering Course

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Abstract

The objective of this work is to present an initial investigation of the impact the Connected Learning and Integrated Course Knowledge (CLICK) approach has had on students' motivation, engineering identity, and learning outcomes. CLICK is an approach that leverages Virtual Reality (VR) technology to provide an integrative learning experience in the Industrial Engineering (IE) curriculum. To achieve this integration, the approach aims to leverage VR learning modules to simulate a variety of systems. The VR learning modules offer an immersive experience and provide the context for real-life applications. The virtual simulated system represents a theme to transfer the system concepts and knowledge across multiple IE courses as well as connect the experience with real-world applications. The CLICK approach has the combined effect of immersion and learning-by-doing benefits. In this work, VR learning modules are developed for a simulated manufacturing system. The modules teach the concepts of measures of location and dispersion, which are used in an introductory probability course within the IE curriculum. This work presents the initial results of comparing the motivation, engineering identity, and knowledge gain between a control and an intervention group (i.e., traditional vs. CLICK teaching groups). The CLICK approach group showed greater motivation compared to a traditional teaching group. However, there were no effects on engineering identity and knowledge gain. Nevertheless, it is hypothesized that the VR learning modules will have a positive impact on the students' motivation, engineering identity, and knowledge gain over the long run and when used across the curriculum. Moreover, IE instructors interested in providing an immersive and integrative learning experience to their students could leverage the VR learning modules developed for this project.

1. Introduction

Like the majority of engineering curricula, the structure of the Industrial Engineering (IE) curriculum consists of a set of courses that are ordered in a sequence such that later courses build upon the knowledge learned in the earlier courses, with each course usually being taught by a different instructor [1]. This traditional course-centric curriculum structure has limited ability to establish the connection between fundamental topics and real-world problems [1,2]. The separation in time and context across different courses could account for this lack of connection [2]. Unfortunately, this lack of connection and understanding could impact students' attrition rates.

The graduation rate of engineering students has stayed consistently around 50% for more than 60 years [3–8]. Some of the many factors that contribute to these low rates include classroom and academic climate (e.g., feeling of engagement and teaching styles), grades and conceptual understanding, self-efficacy and self-confidence, high school preparation, interest, and career goals, and race and gender [9]. Moreover, factors such as low grades and lack of conceptual understanding may drive students away [9]. Hence, there need to be some changes in the current curriculum structure in order to remedy, or at least reduce, the effect of these factors.

Recent improvements to Virtual Reality (VR) hardware coupled with a reduction in cost have resulted in a boom in the use of the technology across a variety of applications [10,11,12]. The potential for VR in education lies in the fact that it enables the creation of immersive simulation-based education, where students can practice new skills in a safe and controlled simulated environment, in which failure is practically risk-free (e.g., learning how to weld without worrying about a fire risk) [10]. VR's strength lies in its ability to create immersion, which is the ability to arouse an experienced reality within the perception of the user [13]. For this reason, VR is considered to have great potential to improve learning by connecting concepts to immersive real-world scenarios [10,11,13].

The limitations in the current curricula combined with the promise of VR for learning inspired the development of the Connected Learning and Integrated Course Knowledge (CLICK) approach, which was introduced in a previous work [14]. This is an approach that leverages VR technology to create learning modules to provide a common theme to connect and transfer knowledge across the IE curriculum, as well as ground the students' conceptual understanding in real-world applications. Instructors can leverage the VR learning modules to teach students IE concepts while providing them an immersive and integrative learning experience. The VR learning modules can be used as a case study, an assignment, or can be embedded in the lectures to teach the concepts. The VR learning modules involve instructions material to teach the main concepts (e.g., what is the mean and how it can be calculated), and provide the environment to collect the necessary data needed to implement the learned concepts (e.g., calculating the mean of a variable and verifying the answer).

In this work, the effectiveness of the CLICK approach for teaching statistical concepts in a junior-level probability and statistics course compared to a control group is explored. The results indicate that the VR learning modules tested in this work had a positive effect on students' motivation, but no significant effect on their engineering identity and knowledge gain. However, the findings and lessons learned from this work will help in the development of future VR learning modules that will be used to test the effects of the CLICK approach when used across the curriculum.

2. Literature Review

The goal of curriculum integration is to make individual courses integrated parts of a whole, connected, and have a common theme of knowledge [19]. The connection should go beyond traditional concurrent and prerequisite connection and instead aim to achieve a common goal. Only a limited number of studies have investigated the overall integration of a curriculum [1]. An interest in studying the idea of integrating courses across the entire curriculum is growing in the research community. The idea is not to integrate all content in all courses, but to have a common theme across the courses instead of focusing on teaching courses as separate entities [1].

The wide array of courses in current engineering curricula are taught by different instructors, and the burden of transferring knowledge between courses and connecting concepts lies on the student. This structure often leads to students struggling in later courses [1]. The responsibility of transferring the knowledge and identifying the connections between courses should be placed on the curriculum instead of the students, as suggested by Maciejewski et al. [2].

Engineering curriculum integration has been shown through multiple studies to have desirable outcomes [20–22]. Evans [21] showed that grades improved, Felder et al. [20] reported increased student satisfaction, while Olds & Miller [22] showed positive reactions from students. A pair of studies that examined Mechanical Engineering students' performance with an integrated four-course curriculum over two years showed improved motivation to stay in school, benefits for non-traditional student learning, and increased knowledge retention [23,24], which indicates an overall performance improvement over a three-year period.

At Auburn University, the Department of Industrial and Systems Engineering introduced a laboratory called the automotive manufacturing systems lab [31], in which students build Lego vehicles and learn about Toyota production system principles. This is an example of direct hands-on experience that is valuable for connecting concepts to real-world scenarios. However, this lab requires a large amount of space (4,000 ft^2) [32] and at least 18 students to run an experiment [33]. However, VR technology can be used to build virtual systems that resemble real-life systems [11,34]. Hence, the authors hypothesize that the CLICK approach can leverage VR technology to provide an affordable alternative that can approximate this valuable hands-on experience. VR technology is used as an education or training aid in many domains, including the military and medical practice [10, 25]. VR can provide a valuable surrogate to real-life experience due to its ability to provide the sense of "being there" [26] and create a "first-person" experience [27,28]. This immersive experience is valuable as a safe way for learners to make mistakes in applications where they can be expensive or dangerous [10,13,29,30]. Moreover, VR is portable, i.e., not limited to residential courses and usable with online learning. Given that online learning continues to be a growing trend [11,12,35–38], this is a considerable advantage offered by VR.

In addition to simulating these practical and expensive environments, VR has been used to teach more abstract mathematical concepts by allowing students to virtually visualize them. Vogel et al. [15] found that a group of students aged 7 to 12 who were taught using VR computer-assisted instruction significantly outperformed a control group on a mathematics test, but had no significant difference in language arts skills. Pasqualotti and Freitas [17] showed that a VR modeling environment improved the scores of 7th grade students on mathematics and geometry normally taught to 8th grade students by allowing students to manipulate objects in first-person and understand their geometric properties. Wang et al. [18] showed that college engineering students who were introduced to a VR mathematics learning module in their math course believed that the module could help them in their math learning and increase their interest in engineering programs. These works show that in addition to providing immersive practical applications of concepts, VR also provides benefits in visualizing abstract concepts and can increase the motivation of students. Moreover, VR enhances visualization, interaction, and collaboration compared to traditional learning [39], and has been shown to enhance students' understanding of concepts while reducing misconceptions [40]. VR allows students to manipulate objects in real-time compared to traditional teaching methods that suffer from a distance, time, or safety constraints [41–43].

The Accreditation Board for Engineering and Technology (ABET) organization says that the IE curriculum focuses on preparing "*graduates to design, develop, implement, and improve* *integrated systems* *that include people, materials, information, equipment, and energy. The curriculum must include in-depth instruction to accomplish the integration of systems using appropriate analytical, computational, and experimental practices*" (www.abet.org [44]). It can be seen from this statement that a major focus of the IE discipline is understanding integrated systems. Given the complexity of these systems, it is paramount that students understand the "big picture" in addition to individual concepts in order to prepare them for real-world problems [2]. A course-centric curriculum structure limits both the ability of students to connect concepts across courses as well as connect them to real-life scenarios [2]. A result of this is that the connection between theory and practice is weak or even missing [45]. The CLICK approach aims to bridge this gap by tying concepts to a common set of virtual environments that mimic real-world scenarios. Specifically, by using VR learning modules that simulate virtual systems that are used as a common theme across multiple courses in the IE curriculum. The objective is to connect the knowledge across different courses as well as real-world applications by providing a context for the topics that students are learning in the class. For more information about the CLICK approach, the reader is referred to the following references [47,48].

As VR, Augmented Reality, and online learning continue to transform the educational landscape [11,12,35,36], the CLICK approach will align even more naturally with these evolving course structures. In this work, VR is leveraged to create immersive learning modules for probability and statistics that mimics a real-life manufacturing setting. However, the modules can be used in different courses across the IE curriculum to transfer and connect systems concepts. The authors hypothesize that students' motivation, engineering identity, and conceptual understanding will improve through the implementation of the CLICK approach by providing a connection of concepts taught in the course to real-life scenarios.

3. The Impact of CLICK Approach

3.1 Virtual System

In this work, an immersive 3D virtual environment that simulates a drill manufacturing system is used for the VR learning modules implemented. This system was selected because it was easy to understand but complex enough to add the necessary pedagogical components now and in the future. Moreover, a similar system was already used in other studies[49]. The virtual environment was built using the Unity game engine [46]. The virtual environment was run on an Oculus Quest device [50]. Oculus Quest was chosen for its portability (i.e., no need for a VR-ready computer machine to run the application), and relative affordability (i.e., starting at $399) compared to wired VR headsets; thus scalability should not be a major issue [50]. This is a key element for instructors interested in implementing and leveraging the VR teaching modules developed for the project. Moreover, the Oculus Quest has the option to run the VR application on a computer in case higher fidelity and computation capability are needed [51].

The virtual environment simulates the initial stages of the manufacturing system. The system involves two injection molding machines, conveyor belts to transfer the drill housings, robotic arms that remove potential defective parts when they pass through the inspection station, and finally, the good parts are moved to a secondary assembly station. Students can collect the process times data, such as time between generated housings, and the number of defective parts. The objective is to help students learn about fundamental statistics concepts (i.e., mean, median, and mode) by allowing them to collect data from the simulated manufacturing system and perform the corresponding calculations to verify their learning. The students can interact with the objects on the manufacturing floor, such as speeding up the injection molding machine and picking up parts. Figure 1 shows snapshots from the virtual environment.

Figure 1. Snapshots from the virtual environment

3.2 Course

This study aims to assess the learning effectiveness and the impact of the CLICK approach in a fundamental probability and statistics course. The course is required for all IE students in their junior year. The students learn probability theory and models and discrete and continuous probability distributions. Other topics include sampling distributions, point and interval estimation of mean, variance, and proportion. This course was selected for the initial study due to the fact that many senior-level IE courses build on concepts introduced in this course, allowing for a follow-up study, and the fact that VR has shown promising results in teaching mathematical concepts across many levels of education [15–18].

The virtual environment includes modules to teach the concepts of mean, median, mode, variance, discrete, and continuous probability distributions (e.g., Poisson, Exponential, and Normal). At the time of collecting the data, the mean, median, and mode learning modules were finalized, but the rest of the modules were still being developed. Hence, the participant only interacted with the mean, median, and mode learning modules.

3.3 Experiment

3.3.1 Experiment Setup and Instruments

The study compared two educational settings: one without the use of the VR learning modules (control group) and the other with the use of the VR learning modules (intervention group). Both groups were taught by the same instructor, and the courses had the same learning objectives and learning material; however, the intervention group's material was supplemented by the VR learning modules. The modules were used during one class session at the end of the semester. Figure 2 outlines the experimental procedure. Both groups of students were enrolled in a fundamental probability and statistics course within the IE curriculum. Since this course has only one section and is taught only during the fall semester, the control group was taught in Fall 2018, and the intervention group was taught in Fall 2019. Table 1 shows the instruments used throughout the experiment, along with the time of use. To establish a baseline and ensure the two groups were statistically comparable (i.e., support groups' homogeneity), demographics, preparation level, personality types, and VR and gaming experience levels were collected at the start of the course (see Figure 2 and Table 1).

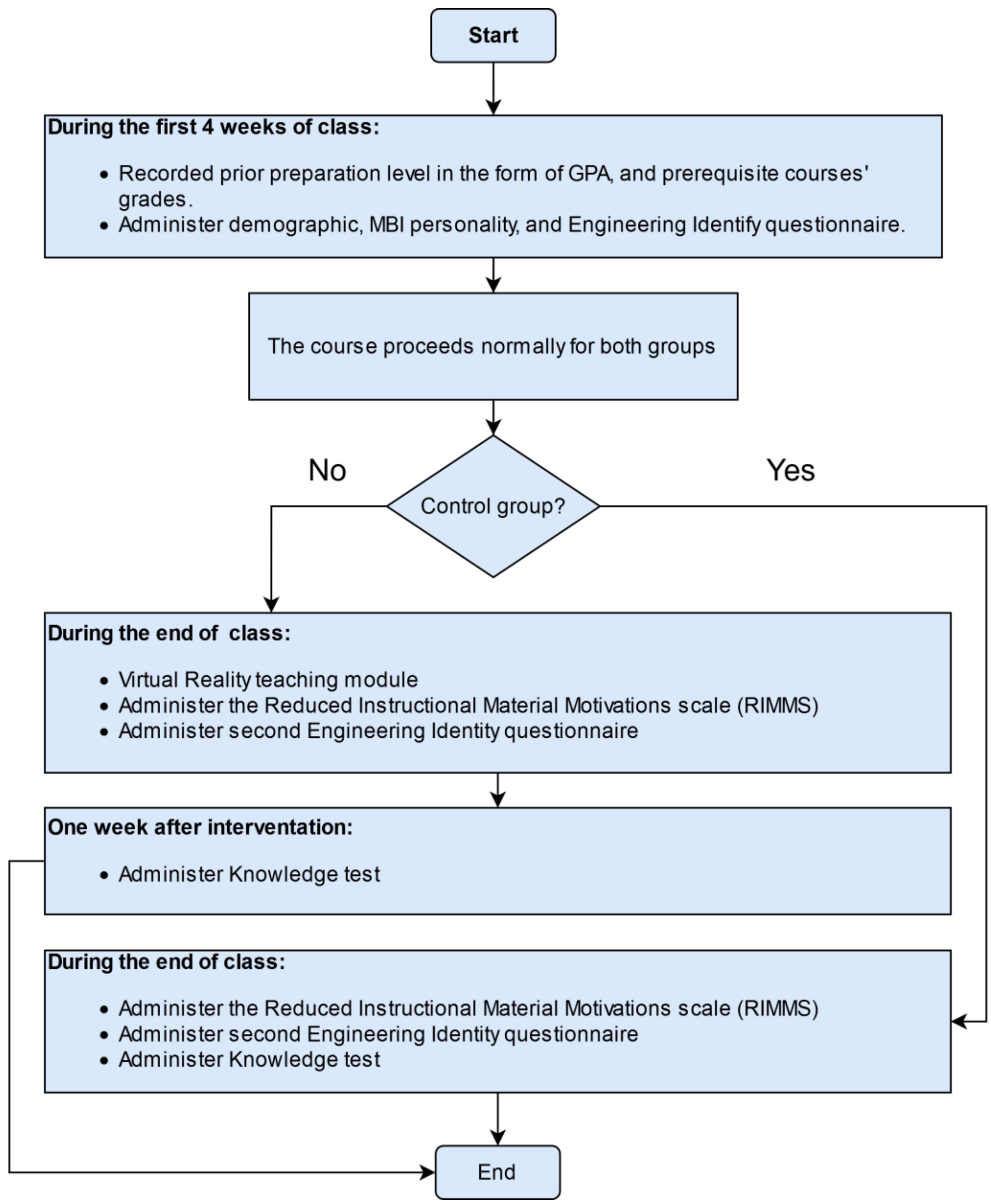

Figure 2. Experimental protocol used

Table 1. The instruments used in this study

Instrument	Description	Event Time
Demographics	Collects demographic information such as age, gender, and race. It also collects information about the student preparation level (GPA and the prerequisite course(s) grade(s)), semester standing, and virtual reality and gaming experience levels	At the beginning of the semester in the course
Myers-Briggs Type Indicator	A questionnaire used to determine the students' personality type. It involves 70 questions. It was designed to identify sixteen patterns of actions and attitudes. The MBTI consists of four scored scales to measure the following eight preferences: Extraversion (E)-Introversion (I), Thinking (T)-Feeling(F), Judging(J)-Perception(P), and Sensing(S)-Intuition(I) [52]	At the beginning of the semester in the course
Engineering Identity	Engineering identity is considered a significant indicator of educational and professional persistence or retention [53]. It is an indicator of how a student considers or sees himself/herself as an engineer. This instrument is divided into three constructs: Recognition (3 items), Interest (3 items), and Performance/Competence (5 items) [53].	At the beginning and the end of the semester in the course
Reduced Instructional Materials Motivation Scale (RIMMS)	Reduced Instructional Materials Motivation Scale (RIMMS). This instrument is used to assess the level of student motivation. It involves a 12-item questionnaire. This is a reduced version of John Keller's ARCS motivational model. It measures four motivation factors from the ARCS model: Attention, Relevance, Confidence, and Satisfaction [54].	At the end of the semester in the course. After the intervention for the intervention group
Knowledge Test	This measure includes a test that was developed to measure the students' understanding of core probability and statistics concepts. The test covered the topics of: (i) discrete probability distributions, (ii) continue probability distributions, (iii) Poisson distribution, (iv) Normal distribution, (v) mean, (vi) standard deviation, and (vii) confidence intervals. The knowledge test was composed of 14 multiple-choice questions. Following Blooms' taxonomy [55], two questions per concept were created, one that required lower-order thinking skills (e.g., define, recall) and one that required higher-order thinking skills (e.g., evaluate, analyze).	At the end of the semester in the course. After the intervention for the intervention group

3.3.2 Participants

A total of 47 Industrial Engineering (IE) students from The Pennsylvania State University, The Behrend College participated in this experiment. The control group was composed of 24 students (58.3% males) who registered for the fundamental probability and statistics course during the Fall 2018 semester. The intervention group was composed of 23 students (52% males) who registered for the same course during the Fall 2019 semester. The students in both groups completed a series of surveys and questionnaires (see Figure 2 and Table 1). Table 2 shows the summary statistics of the results from the demographics, experience, and personality questionnaires.

The results from a multiple chi-squared test indicate that the proportion of participants with different gender identity, ethnicity, gaming experience level, VR experience level, and personality traits did not differ between groups, at an alpha level of 0.05. Similarly, the results of a t-test show that the mean GPA of the control group (M=3.10, SD=0.40) was not statistically significantly different than the mean GPA of the intervention group (M=2.84, SD=0.55), at an alpha level of 0.05. All these results indicate that the participants on the control and intervention groups, on average, were not significantly different based on these measurements.

Table 2. Summary statistics of the demographics, experience, and personality

	Total		Control		Intervention	
	Freq.	*Prop.*	*Freq.*	*Prop.*	*Freq.*	*Prop.*
<u>Gender Identity</u>						
Female	20	0.43	9	0.38	11	0.48
Male	26	0.55	14	0.58	12	0.52
Other	1	0.02	1	0.04	0	0.00
<u>Ethnicity</u>						
Caucasian	34	0.72	15	0.63	19	0.83
Hispanic	3	0.06	3	0.13	0	0.00
Asian or Pacific Islander	6	0.13	3	0.13	3	0.13
Middle Easterner	2	0.04	2	0.08	0	0.00
African American	2	0.04	1	0.04	1	0.04
<u>Program Level</u>						
Junior	38	0.81	21	0.88	17	0.74
Senior	9	0.19	3	0.13	6	0.26
<u>Gaming Experience</u>						
None	8	0.17	4	0.17	4	0.17
Some	23	0.49	11	0.46	12	0.52
Expert	16	0.34	9	0.38	7	0.30
<u>VR Experience</u>						
None	14	0.30	9	0.38	5	0.22
Some	31	0.66	15	0.63	16	0.70
Expert	2	0.04	0	0.00	2	0.09
<u>Personality trait</u>						
Extrovert	20	0.43	12	0.50	8	0.35
Introvert	27	0.57	12	0.50	15	0.65
Intuitive	16	0.34	7	0.29	9	0.39
Sensitive	31	0.66	17	0.71	14	0.61
Thinking	37	0.79	20	0.83	17	0.74
Feeling	10	0.21	4	0.17	6	0.26
Judging	36	0.77	17	0.71	19	0.83
Perceiving	11	0.23	7	0.29	4	0.17

[1]The Personality trait was assessed with the Myers-Briggs Type Indicator (MBTI) 48 questions test [52]. The MBTI reports the dominant trait of an individual on four categories (i.e., Extrovert/Introvert, Intuitive/Sensitive, Thinking/Feeling, Judging/Perceiving).

3.3.3 Results and Discussions

Table 3 shows the summary statistics of the dependent variables analyzed in this work. A series of independent t-test (t) and non-parametric Wilcoxon tests (w) were performed to evaluate if there was a significant difference between the control and intervention groups. The non-parametric Wilcoxon test was performed on the cases where the assumption of normality could not be supported by the results of a Shapiro-test for normality with an alpha level of 0.05.

Table 3. Statistical analysis summary of the dependent variables

	Total			Control			Intervention			
	M	*Mdn*	*SD*	*M*	*Mdn*	*SD*	*M*	*Mdn*	*SD*	*Stat.*
RIMMS[1]										
Attention	10.97	11.00	2.02	10.53	11.00	2.37	11.35	11.50	1.63	*w*-
Relevance	11.26	12.00	2.23	12.06	12.00	1.92	10.62	11.00	2.29	*w*-
Confidence	12.11	13.00	2.01	11.47	12.00	1.81	12.62	13.00	2.06	*w*′
Satisfaction	11.87	12.50	2.53	10.35	10.00	2.69	13.10	13.00	1.58	*w****
Overall=	46.03	48.00	6.90	44.41	47.00	8.16	47.40	48.50	5.47	*w* -
1st Eng. Identity[2]										
Recognition	13.36	14.00	2.89	12.83	13.00	3.05	13.91	15.00	2.68	*w*-
Interest	14.78	15.50	2.96	14.17	14.00	3.34	15.45	16.00	2.36	*w*-
Performance	20.96	21.00	4.80	21.38	24.00	4.79	20.52	21.00	4.89	*w*-
Overall=	48.98	50.00	8.73	48.38	49.00	9.19	49.64	51.00	8.36	*w*-
2nd Eng. Identity[3]										
Recognition	16.58	16.50	3.51	18.53	18.00	3.39	15.00	15.00	2.77	*t**
Interest	18.26	18.00	3.22	20.88	21.00	2.47	16.14	17.00	1.93	*t****
Performance	27.03	27.50	5.38	30.94	31.00	4.10	23.86	25.00	4.07	*t****
Overall=	61.87	63.00	10.77	70.35	70.00	7.30	55.00	56.00	7.84	*t****
Eng. Identity Diff.[4]										
Recognition	3.11	2.50	3.70	5.41	4.00	3.79	1.24	1.00	2.36	*t****
Interest	3.27	3.00	3.28	6.06	6.00	2.11	0.90	0.00	1.94	*t****
Performance	5.82	5.00	5.45	9.12	8.00	5.53	3.14	3.00	3.69	*t***
Overall=	12.38	10.00	11.28	20.59	18.00	10.01	5.40	5.00	6.71	*t****
Knowledge Test[5]										
Lower order skills	3.98	4.00	1.32	4.30	4.00	1.36	3.65	4.00	1.23	*w*-
Higher order skills	2.98	3.00	1.16	2.96	3.00	1.30	3.00	3.00	1.04	*w*-
Overall=	6.96	7.00	2.04	7.26	7.00	2.09	6.65	7.00	1.99	*t*-

[1]RIMMS questionnaire requires users to rate a set of 12 statements using a 5-point Likert scale. Each of the RIMMS items are based on the responses of 3 statements (i.e., max= 15). RIMMS is calculated based on the sum of all its items (i.e., max=60) [54]. The control and intervention groups completed the RIMMS questionnaire on week 15 of the semester; the intervention group completed the questionnaire immediately after the intervention (see sections 3.3.1).

[2]The Engineering Identify questionnaires require users to rate a set of 11 statements using a 6 point-Likert scale. The item of Recognition and Interest is calculated based on the responses of 3 different statements (i.e., max= 18), while the item of Performance is calculated based on the responses of 5 different statements (i.e., max= 30). Engineering Identify value is calculated based on the sum of all its items (i.e., max=66) [53]. The control and intervention groups completed the 1st Engineering Identify questionnaires on week 4 of the semester (see sections 3.3.1).

[3]The control and intervention groups completed the 2nd Engineering Identify questionnaires on week 15 of the semester; the intervention group completed the questionnaire immediately after the intervention (see sections 3.3.1).

[4]The difference between the participants' responses on the 1st and 2nd Engineering Identify questionnaires is calculated by subtracting the individual responses of the 2nd minus the 1st questionnaires.

[5]The knowledge tests were composed of 14 multiple choice questions (i.e., max points=14), 7 questions that required lower-order thinking skills, and 7 that required higher-order thinking skills.

[†]The statistics columns shows the test that was performed: independent t-test (t) or non-parametric Wilcoxon test (w), as well as the p-value of the statistic: >0.05 (-), <0.05(‘), <0.01(*), <0.001(**), <0.001(***). The non-parametric Wilcoxon test was performed on the cases where the assumption of normality could not be validated via a Shapiro-test for normality

Reduced Instructional Materials Motivation Scale

The results from the Reduced Instructional Materials Motivation Scale (RIMMS) questionnaire show that participants in the intervention group reported greater motivation after interacting with the VR modules ($M=47.40$, $SD= 5.47$) than participants in the control group after using traditional learning materials ($M=44.41$, $SD= 8.16$). However, the results of the Wilcoxon test do not indicate that this difference was statistically significant at an alpha level of 0.05.

When looking at the elements of the RIMMS, the results show that participants in the intervention group reported greater Attention, Confidence, and Satisfaction than the control group. The results of the Wilcoxon test indicate that the reported RIMMS Confidence (p-value=0.04) and Satisfaction (p-value=0.0007) elements were statistically significantly different between the groups. The RIMMS results indicate that the VR learning modules were perceived as more motivational than the traditional learning materials. This despite the fact that several of the participants encountered difficulties interacting with the VR headset even after the initial training. Moreover, participants' low response to the element of Relevance could be potentially attributed to the fact that the VR learning modules only covered three basic statistics concepts (i.e., mean, median, and mode submodules). In addition, the VR learning modules suffered from some bugs that made it difficult to finish the activities at times.

Engineering Identify

With regards to the Engineering Identity questionnaire completed at the beginning of the semester, the results of the independent t-test indicate there was no statistically significant difference between the participants' responses in the control and intervention group, at an alpha level of 0.05. This indicates that the participants on the control and intervention groups, on average, were not significantly different, similar to the results presented in section 3.3.2. When looking at the Engineering Identity questionnaires completed at the end of the semester, the results indicate an increase for both groups. The results of the paired t-test indicate that participants in the control group ($M=20.59$, $SD=10.01$, p-value<0.001) and in the intervention group ($M=5.40$, $SD=6.71$, p-value=0.0019) reported a statistically significant increase in Engineering Identity. Moreover, the results of an independent t-test indicate this increase was statistically significantly different between the groups (p-value<0.001). The results indicate a similar trend for all the elements of the Engineering Identity questionnaire.

When comparing the responses for the second Engineering Identity questionnaire, the results of the independent t-test indicate there was a statistically significant difference (p-value<0.001) between the responses of participants in the control ($M=70.35$, $SD=7.30$) and in the intervention group ($M=55.00$, $SD= 7.84$). All these results suggest that while students reported an increased Engineering Identity at the end of the semester, the intervention did not have positive effects on it. In contrast, the intervention of using the VR learning modules could have had a negative effect when compared to traditional learning material. While it was hypothesized that allowing IE students to learn and solve problems in a virtual environment would have helped them in the field identified with their profession (i.e., increased Engineering Identity), the results of this work do no support this hypothesis. This could be potentially attributed to the fact that students only interacted with a manufacturing system. Hence, students interested in other IE areas (e.g., service, healthcare) may not have felt identified with this manufacturing system. These results could also be attributed to the issues that some of the students experienced while using the VR learning modules.

Knowledge Test

Finally, when looking at the knowledge tests, the results of a paired t-test reveal there was a statistically significant difference between students' score on the lower order thinking skills questions and higher-order skills questions for both the control (M=1.35, SD=1.64, p-value=0.0007) and the intervention group (M=0.65, SD=1.11, p-value=0.01). Moreover, the results of an independent t-test show the difference in score between the lower and higher-order skills questions was not statistically significant between the groups (p-value=0.1004). Similarly, the independent t-test results show there was no statistically significant difference between the final test score of the groups (p-value=0.3179).

These results suggest the intervention of the VR learning modules did not have a significant impact on student performance on the knowledge test. This could potentially be attributed to the fact that the VR learning modules only covered the concept of mean, median, and mode, while the knowledge tests covered a wider range of statistical concepts. However, even when only considering the questions related to the mean, the results of the non-parametric Wilcoxon test show that there was no statistically significant difference between the groups (p-value=0.69).

4. Conclusions, Limitations, and Future Works

This work presents the initial results of investigating the impact of the CLICK approach on students' learning, motivation, and engineering identity in a fundamental probability and statistics course. Towards this objective, VR learning modules to teach fundamental probability and statistics within the IE curriculum were developed and implemented in a controlled experiment. The results of the experiment indicated that the VR learning modules improved the students' motivation, more specifically in terms of confidence and satisfaction as compared to the traditional teaching approach. However, the results indicate that the use of the VR learning modules did not have an effect on students' engineering identity and knowledge gain.

This work represents the first step in assessing the impact of the CLICK approach, i.e., VR learning modules across multiple courses in the IE curriculum, on students' learning, engineering identity, and motivation. The findings reveal the impact of the VR learning modules on students' motivation, and the experiment provided valuable insights that will help the authors in the development and improvement of future modules. However, several limitations and challenges were faced and are reported next.

First, the creation of the VR learning modules required more development time and effort than what was initially anticipated. Therefore, many concepts that were intended to be included in the modules were missing, and there was not enough time to thoroughly test them for usability. Second, instructors sometimes are hesitant to try and experiment with new approaches during class time, fearing that this time will be wasted and might impact how much material they will cover during the semester. The original plan of the experiment included the use of the VR learning modules multiple times in the class throughout the semester, but due to the above-mentioned challenges, the authors implemented the experiment at the end of the semester. The use of any new technology in the classroom will face similar challenges. This is because some people's innate nature is to avoid and resists change, even if the change will ultimately benefit them and the learning process and outcomes (e.g., resistant to implementing computers in the classroom). Third, the VR learning modules were developed for a manufacturing system. Some students might prefer to interact with other types of systems, such as healthcare or service systems. This may have impacted the results of engineering identity as well as motivation. Fourth, even though the students were given a training tutorial on how to use the VR learning modules at the start of the experiment, many students indicated they needed more time to interact smoothly with the environment. Fifth, the experiment was conducted in a regular classroom and 13 students were using the VR headsets with external speakers at the same time. This setup could have created some distracting noises; hence, headphones should be used in the future to avoid this situation. Finally, while having the same instructor teach both groups could reduce the inconsistency in teaching styles, time spent on concepts, etc., the instructor's knowledge of the experiment might have introduced bias (positive or negative) in the results. The implementation of this approach at different schools and settings will reduce this bias.

Future work will focus on collecting more data by testing the learning modules in other higher-ed institutions. The VR learning modules will be available to the public through the project website (www.clickapproach.org). Moreover, future VR learning modules will include more core concepts and will go through an iterative testing procedure to ensure their usability and that they are free of bugs. The VR learning modules will also be used multiple times throughout the semester, and students will be given enough time to learn how to use the modules and how to interact with the concepts. A tutorial video will be created and sent to the students before the experiment time. Finally, other VR learning modules that involve different types of systems will be developed to accommodate students' preferences, and the team will implement them in other courses of the IE curriculum. While there were several challenges and limitations, the results of this work show that the CLICK approach helped improve students' motivation compared to a traditional teaching group. Moreover, instructors that have access to VR headsets can leverage these learning modules to teach students IE concepts while providing them an immersive and integrative learning experience.

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