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A Study on the Effectiveness of the CLICK Approach in an Operations Research Course

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Abstract

This paper presents an investigation of the effectiveness of the connected learning and integrated course knowledge (CLICK) approach. The CLICK approach aims to integrate the knowledge across the industrial engineering (IE) curriculum by leveraging immersive technology, i.e., 3D simulation and virtual reality (VR). The effectiveness of the CLICK approach is measured by its impact on students' motivation, engineering identity, and learning outcomes. In this work, a virtual system that simulates a manufacturing assembly system was developed and used in an operations research (OR) course. The virtual system includes data collection tasks and exercises to calculate statistics that are taught in a probability and statistics course, and inventory and queueing theories concepts that are taught in an operations research course. The virtual system (CLICK learning module) is used to teach inventory and queueing theory concepts. Due to COVID-19 and the sudden shift to remote learning, the research team faced challenges including limitations in performing in-person experiments on campus as well as the potential risk of spreading the disease when VR headsets are used by several people. To alleviate some of the challenges, the researchers built the virtual system in simulation software, i.e., Simio, to provide more flexibility and scalability. The virtual system can be run on a regular personal computer without the need for a VR-ready computer and VR headsets. Yet, the virtual system can be run on an Oculus VR headset if the student prefers to do so.

The study involves two groups: Control and intervention groups. The control group is represented by the students who are taught traditionally while the intervention group is represented by the students who are taught with the aid of the CLICK learning module. The results of this study compared the groups in terms of students' motivation, and engineering identity. The learning outcomes were assessed using a self-assessment instrument and the student's grades in the learning module. The data of the control and intervention groups were collected at Penn State Behrend in Fall 2019, and Fall 2020 semesters, respectively. The groups were not statistically significantly different for motivation and Engineering Identity, however, the resulted motivation and Engineering Identity scores for the intervention group were not worse than the control group considering the shift to remote learning setting. The students showed good learning outcomes when the CLICK learning module was used. The grades were positively correlated to the motivation and Engineering Identity scores.

1. Introduction

Engineering curricula are typically structured as a set of sequential courses (often taught by different instructors) where later courses build upon the knowledge gained from the earlier courses [1]. The Industrial Engineering (IE) curriculum is no exception. One limitation of this traditional approach is that the separation in time and context across different courses can make it difficult for students to connect fundamental topics to real-world problems[2]. This lack of connection is a potential factor that impacts engineering students' attrition rates. Engineering students have graduated at a rate of about 50% for more than 60 years [3]–[8]. Many factors contribute to these low rates of graduation, including 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, as well as low grades and lack of conceptual understanding [9]. To reduce these poor attrition rates, there must be some changes to the way that the engineering curriculum is delivered.

The limitations in the current engineering curricula for learning inspired the development of the Connected Learning and Integrated Course Knowledge (CLICK) approach, which was introduced in previous work [10]. This is an approach that leverages immersive technologies including 3D simulation and Virtual Reality (VR) to create learning modules that not only relate concepts in the industrial engineering (IE) curriculum to a common theme but also connect the conceptual topics to real-world applications. Virtual systems can be embedded into the course in lectures, assignments, or both, and allow for students to collect necessary data to implement a concept, as well as see the concept applied to a real-world scenario. Using virtual environments also provides the benefit of providing real-world demonstration with significantly reduced effort and cost to a physical environment in many cases (for example, a manufacturing facility) as well as less risky situations [11], [12].

In this work, the effectiveness of the CLICK approach is investigated with regards to teaching in an Operations Research (OR) course. The results indicate that there was no overall difference in motivation between the control and intervention groups, however, students in the intervention group reported improved confidence in the concepts and were able to accurately assess their understanding of the concepts in the virtual learning module. Students in the intervention group showed no decrease in motivation and engineering identity scores, although it should be noted that the intervention group’s course was interrupted by the COVID-19 pandemic while the control group was not. More details on the hypothesized effect of this interruption are provided in Section 3. Feedback on the usability of the virtual learning module was solicited from the students that provided valuable insight on how to improve the learning module in future experiments.

2. Literature Review

Curriculum integration aims to structure individual courses as integrated parts of a whole that are connected and maintain a common theme of knowledge [13]. The goal is that the connection goes beyond traditional concurrent and prerequisite relationships between courses and instead connects the courses via a common theme. While only a limited number of studies have investigated the overall integration of a curriculum, an interest in studying the idea of integrating courses across the entire curriculum is growing in the research community [1].

Currently, the wide array of courses in an engineering curriculum are taught by different instructors, placing the burden of transferring knowledge between courses and connecting concepts on the student. This structure has been shown to lead some students to struggle in later courses [1]. Integrated course curricula aim to place the burden of transferring the knowledge and identifying the connections between courses should on the curriculum instead [2].

Engineering curriculum integration has been shown through multiple studies to have various desirable outcomes [14]–[16]. Evans [15] demonstrated improved grades, Felder et al. [14] reported improved student satisfaction, while Olds & Miller [16] showed positive reactions from students. One pair of studies by Everett et al. and Felder et al. respectively investigated Mechanical Engineering students' performance with an integrated four-course curriculum over two years [17], [18]. They showed improved motivation to stay in school, benefits related to non-traditional student learning, as well as increased knowledge retention, indicating an overall performance improvement over three years.

The Department of Industrial and Systems Engineering at Auburn University created the automotive manufacturing systems lab [19], where students were able to build LEGO vehicles and learn about Toyota production system principles. This is an example of related course concepts to real-world problems using physical examples. However, this lab requires 4,000 ft^2 of space [20] and at least 18 students to run an experiment [21]. In contrast, virtual systems can be constructed to resemble real-life systems without the same cumbersome requirements [22], [23]. Hence, the authors hypothesize that simulation environments can be used to approximate the benefits of valuable hands-on experience in a more affordable manner.

Virtual systems built using immersive technologies such as 3D simulation and VR environments are used in many fields to give students hands-on experience in a low-risk affordable way, including medicine [24]–[26], the military [27]–[29], and engineering [22], [23], [30]. According to Hamalek et al. [25], the goal of these virtual simulation environments is to create a sense of immersion of the student in a realistic scenario that replicates a real-world environment with fidelity sufficient to achieve suspension of disbelief on the part of the student. In Deshpande et al.'s [23] review of simulation games in engineering education, they found many advantages of teaching engineering concepts through simulated environments over traditional classroom instruction, including but not limited to connecting theory to practice, customizability of difficulty to match students comprehension level, reduction of resistance to accepting innovative ideas and concepts, and greater retention of concepts over time. Another advantage of simulation-based learning is its compatibility with online learning, which continues to be a growing trend, especially since the COVID-19 pandemic [11], [18], [31], [32].

Using virtual systems to augment education is not only limited to practical and otherwise expensive real-world environments but can also be used to teach more abstract mathematical concepts by allowing students to visualize them. Bouta et al. showed that an online virtual 3D environment to teach basic fractions to primary school students improved the students' ability to employ versatile thinking strategies and improves engagement [33]. Wang et al.[34] 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. Baglin et al. found that students using a virtual environment for project-based assessment in an online introductory statistics course found it to be engaging and beneficial to the development of their statistical thinking. Additionally, our previous work showed that students who used VR manufacturing environments to learn concepts in an introductory probability course had a higher motivation at the end of the course compared to those who did not [35]. These works show that virtual environments not only provide immersive practical demonstrations of concepts but offer benefits in visualizing abstract concepts and increased motivation in students. Moreover, virtual environments have been shown to enhance interaction and collaboration compared to traditional learning [36] and have been shown to enhance student's understanding of concepts while reducing misconceptions [37].

According to the Accreditation Board for Engineering and Technology (ABET) organization, the IE curriculum focuses on preparing "*graduates to design, develop, implement, and improve* <u>*integrated systems*</u> *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 [38]). From this statement, it can be seen that integrated systems are a critical component of the IE curriculum. Because these systems are complex, students must understand both the "big picture" as well as the individual concepts to be prepared for real-world applications [2]. Because, course-centric curricula are lacking in their ability to help students connect concepts across courses and relate to real-world scenarios [2], the connection between theory and practice is weak or even missing [39]. 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 learning modules that leverage immersive technologies to simulate systems that are used as a common theme across multiple courses in the IE curriculum. The objective is to provide a common context for the topics that students are learning in various IE courses. For more information about the CLICK approach, the reader is referred to the following references [10], [35], [40].

As immersive technologies including VR, Augmented Reality, 3D simulation, and online/remote learning continue to transform the educational landscape [32], [41]–[43], the CLICK approach will align even more naturally with these evolving course structures. In this work, a 3D simulation learning module is used as a second course of an operations research course in the IE curriculum. The simulation environment mimics a real-life manufacturing setting for a table lamp manufacturing assembly facility. However, the module can be used in different courses across the IE curriculum to transfer and connect systems concepts. The CLICK approach aims to improve students' motivation, engineering identity, and conceptual understanding by providing a connection of concepts taught in the course to real-life scenarios. The work presented in this paper is part of an ongoing project to investigate the effectiveness of the CLICK approach in achieving this goal.

3. Effectiveness of the CLICK Approach Study

3.1 Immersive 3D Simulation Learning Module

A 3D simulation model for a manufacturing assembly system was built in Simio® for the learning module. Simio® is a software package that can be used to create and run dynamic models of systems with the ability to build 3D animations [44]. The system represents a table lamp manufacturing assembly environment. Figure 1 shows a snapshot of the environment. The overall process starts with creating the base part of the table lamp using injection molding machines, the base parts are then cooled down and transported to a preparation station via conveyor belts. After preparation, the base parts and the outsourced shade parts are sent to assembly stations to be assembled. The assembled table lamps are then packaged and sent to shipping. The system includes inventories for the base part raw material and the outsourced shades.

The simulation model can be run on a regular computer where students can navigate through the model, collect data such as the table lamps demand, processing times, and percentage of defective table lamps, observe the animation and the system performance measures, and make changes to some of the system's parameters such as the capacity of the resources and inventory policy. In addition, the model can be run on an Oculus Quest or Rift S virtual reality (VR) headsets but that will require a VR-ready computer. To run the model on an Oculus Quest, the headset should be tethered to the VR-ready computer via a USB cable.

Figure 1. Snapshot of the 3D simulation model

The learning objectives of this learning module are:

- Collect necessary data to improve the current system.
- Estimate certain quantities such as the demand for raw material.
- Analyze the current system and assess improvement opportunities.
- Evaluate the flow of the parts in the system and devise a solution(s) to improve the performance of the system.
- Devise an inventory policy that minimizes the total annual inventory cost of raw material.

The following section describes the course in which this learning module was used.

3.2 Course

The learning module was implemented in the second course of Operations Research (OR) in the IE department at Penn State Behrend. The course is required by all students in the baccalaureate degree in Industrial Engineering (IE). The course introduces the modeling of stochastic systems and models. Students learn about inventory models, Markov chains, queueing models, and dynamic programming. This is one of the courses selected to implement the CLICK approach because of the importance of the concepts covered in this course. The authors implemented the CLICK approach in a probability and statistics course last year which is a prerequisite to this course [35]. In the previous study, a VR learning module was implemented as compared to this work. Due to COVID-19 and the sudden shift to remote learning, the research team faced challenges including limitations in performing in-person experiments on campus as well as the potential risk of spreading the disease when VR headsets are used by several people. To alleviate some of the challenges, the researchers built the virtual system using simulation software, i.e., Simio®, to provide more flexibility and scalability. The virtual system can be run on a regular personal computer without the need for a VR-ready computer and VR headsets. Yet, the virtual system can be run on an Oculus VR headset if the student prefers to do so.

The learning module focuses on two topics: Queueing systems and inventory theory. The students were asked to consider the simulation model of the current system as their actual system. The current system suffers from multiple problems including high work in process inventory, poor inventory policies, poor customer satisfaction, long cycle time, and high costs. The students are asked to identify these problems, make decisions, and recommend solutions to improve the efficiency of the system as well as lower costs. The students can make changes in the system parameters such as resource capacity and inventory policy. In addition, the students can fast-forward the run to observe the impact of their decisions on the performance measures of the system such as customer satisfaction and cycle time.

3.3 Study Experiment

3.3.1 Experimental Setup and Instruments

To study the effectiveness of the CLICK approach in this course, data collected for two groups: the Control group, and the intervention group. The students in both groups were taught by the same instructor, course material, and learning objectives. Both groups were asked to work on case studies. The control group worked on two case studies throughout the semester while the intervention group worked on the immersive 3D simulation learning module that was assigned four weeks before the end of the semester. Figure 2 shows the overall experimental procedure followed in this study. This course is taught once a year, thus the control group data was collected in Fall 2019 and the intervention group data was collected in Fall 2020.

The following instruments were used to collect the data:

1) Demographic and prior experience and preparation: Subjects data such as age, gender, and race along with the student's prior preparation and experience levels (i.e., GPA and

the prerequisite course(s) grade(s), semester standing, and virtual reality and gaming experience levels). This data was collected at the beginning of the previous course in this project [10], [35].

2) Myers-Briggs Type Indicator: A questionnaire used to determine the students' personality type. The indicator consists of four scales to measure the following eight preferences: Extraversion (E)-Introversion (I), Thinking (T)-Feeling(F), Judging(J)-Perception(P), and Sensing(S)-Intuition(I) [45]. For more information about the questionnaire, check these references [45], [46].

The demographics, prior preparation, and experience level data were collected to establish a baseline and ensure the two groups were statistically comparable (i.e., support groups' homogeneity).

3) Engineering identity: This instrument is used as an indicator of how a student considers or sees himself/herself as an engineer [47]. The instrument includes three constructs: Recognition (3 items), Interest (3 items), and Performance/Competence (5 items) [47]. This instrument was administered toward the end of the semester.
4) Instructional Materials Motivation Scale (IMMS): This scale is used to gauge student motivation when using an educational instrument. It measures four motivation factors from the ARCS model: Attention, Relevance, Confidence, and Satisfaction [48]. This instrument was administered toward the end of the semester and after finishing the case studies (control group) and the immersive simulation learning module (intervention group).
5) Self-assessment tool (intervention group only): This tool is based on Bloom's Revised Taxonomy [49]. It measures the performance of the students toward achieving the designed learning outcomes.
6) Performance assessment (intervention group only): A rubric was developed to assess the students' achievement of the learning objectives and performance concerning the core concepts.

3.3.2 Participants

A total of 44 students from Penn State Behrend participated in this experiment. The control group was composed of 24 students (58.3% males) who registered for a second course in operation research course during the Fall 2019 semester. The intervention group was composed of 20 students (55% males) who registered for the same course during the Fall 2020 semester. The students in both groups completed a series of surveys and questionnaires (see section 3.3.1 and Figure 2). Table 2 shows the summary statistics of the results from the demographics and experience questionnaires.

The results from multiple chi-squared tests indicate that the proportion of participants with different gender identity, ethnicity, gaming experience level, and VR experience level, and personality traits was not statistically significantly different between the 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=2.93, SD=0.40) was not statistically significantly different than the mean GPA of the intervention group (M=2.96, SD=0.42), 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. This supports the homogeneity of the groups.

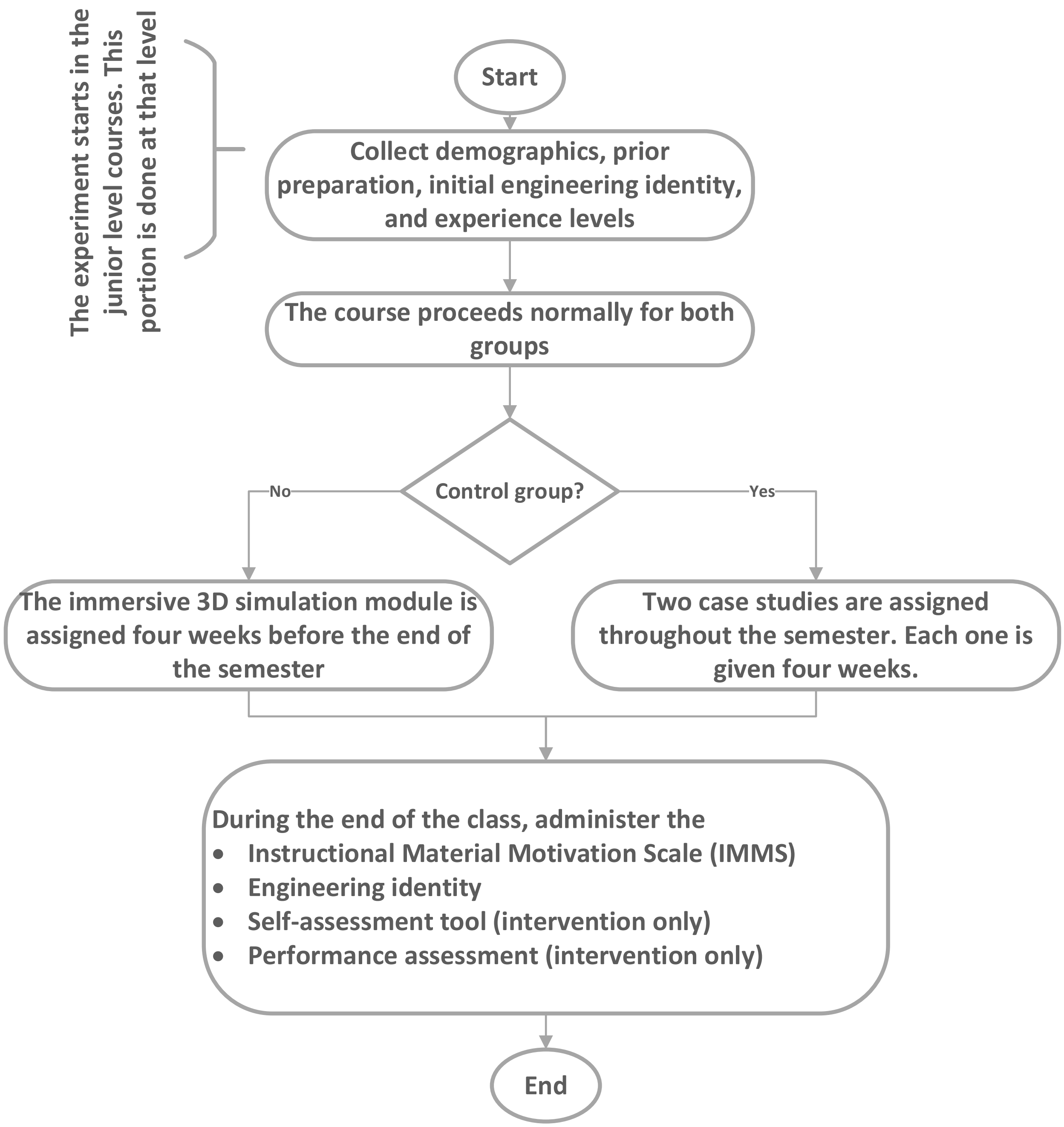


Figure 2. Experimental procedure

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

	Total		Control		Intervention	
	Freq.	*Prop.*	*Freq.*	*Prop.*	*Freq.*	*Prop.*
Gender Identity						
Female	18	0.41	9	0.38	9	0.45
Male	25	0.57	14	0.58	11	0.55
Other	1	0.02	1	0.04	0	0.00
Ethnicity						
Caucasian	30	0.68	15	0.63	15	0.75
Hispanic	4	0.09	3	0.13	1	0.05
Asian or Pacific Islander	6	0.14	3	0.13	3	0.15
African American	1	0.02	1	0.04	0	0.00
Other	3	0.07	2	0.08	1	0.05
Gaming Experience						
None	5	0.11	4	0.17	1	0.05
Some	19	0.43	11	0.46	8	0.40
Expert	20	0.45	9	0.38	11	0.55
VR Experience						
None	17	0.39	9	0.38	8	0.40
Some	27	0.61	15	0.63	12	0.60
Expert	0	0.00	0	0.00	0	0.00
Personality trait						
Extrovert	19	0.43	12	0.50	7	0.35
Introvert	22	0.50	12	0.50	10	0.50
Intuitive	13	0.30	7	0.29	6	0.30
Sensitive	28	0.64	17	0.71	11	0.55
Thinking	31	0.70	20	0.83	11	0.55
Feeling	10	0.23	4	0.17	6	0.30
Judging	30	0.68	17	0.71	13	0.65
Perceiving	11	0.25	7	0.29	4	0.20

3.3.3 Results and Discussions

Table 3 shows the summary statistics of the Instructional Material Motivation Scale (IMMS) and the Engineering Identity questionnaire completed by the control and intervention groups according to the experimental procedure shown in Figure 2. Both groups completed the Engineering Identify questionnaire at the end of the operations research course, as well as at the beginning of the probabilistic models in the industrial engineering course taken two semesters before the operations research course. The probabilistic models in the industrial engineering course was the first course the research team collected data for the CLICK project [35].

Instructional Materials Motivation Scale and System Usability Scale

The results from the Instructional Materials Motivation Scale (IMMS) show that, on average, there was no statistically significant difference in the overall motivation of participants between the groups. However, the results of a Wilcoxon test indicate that the intervention group reported a higher level of confidence than the control group (p-value=0.038, Shapiro-test p-value=0.005). This was the only element of the IMMS questionnaire that showed a significant difference between the groups.

The intervention group also completed a System Usability Scale (SUS) questionnaire after interacting with the 3D simulation. The results indicate that the simulation model could benefit from some improvement. On average, students reported a SUS of 52.13 (Mdn=52.50, SD=20.17, Range = [22.50-85.00]). The results also indicate that participants' SUS and IMMS scores were positively correlated (ρ=0.77, p-value<0.001). It should be noted that the students in this course never had any exposure to the simulation software. Thus, they needed to familiarize themselves with the needed tools to navigate and run the simulation model.

Table 3. Statistical analysis summary of the dependent variables

	Control			Intervention		
	M	*Mdn*	*SD*	*M*	*Mdn*	*SD*
IMMS[1]						
Attention	10.17	11.00	2.42	9.9	10.50	3.29
Relevance	10.79	11.00	2.43	10.65	11.50	2.64
Confidence	10.83	11.00	2.26	12.00	13.00	2.51
Satisfaction	10.04	10.00	2.76	8.95	9.00	2.91
Overall=	41.83	43.00	9.06	41.50	43.50	10.55
Initial Engineering Identity[2]						
Recognition	12.83	13.00	3.05	13.91	15.00	2.68
Interest	14.17	14.00	3.34	15.45	16.00	2.36
Performance	21.38	24.00	4.79	20.52	21.00	4.89
Overall=	48.38	49.00	9.19	49.64	51.00	8.36
Final Engineering Identity[3]						
Recognition	14.62	15.00	3.12	15.85	16.00	1.76
Interest	16.33	18.00	2.91	15.60	16.00	4.49
Performance	24.96	25.00	4.45	23.90	25.00	4.47
Overall=	55.92	57.50	9.96	55.35	55.00	7.49
Engineering Identity Diff. [4]						
Recognition	2.05	2.00	2.95	1.71	1.00	2.71
Interest	2.52	1.00	2.89	0.06	0.00	3.17
Performance	3.58	2.00	4.33	3.88	3.00	3.65
Overall=	8.16	8.00	7.94	5.65	4.00	6.65

[1]IMMS questionnaire requires users to rate a set of 12 statements using a 5-point Likert scale. Each of the IMMS items is based on the responses of 3 statements (i.e., max= 15). IMMS is calculated based on the sum of all its items (i.e., max=60) [48]. The control and intervention groups completed the IMMS 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 questionnaire requires 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) [47]. The control and intervention groups completed the initial Engineering Identify questionnaires on week 4 of their probabilistic models in the industrial engineer course.

[3]The control and intervention groups completed a final Engineering Identify questionnaire on week 15 of their stochastic modeling in the operations research course, two semesters after completing their initial Engineering Identify questionnaire.

[4]The difference between the participants' responses on their Engineering Identify questionnaires is calculated by subtracting the individual responses (i.e., within-subject difference).

Engineering Identity

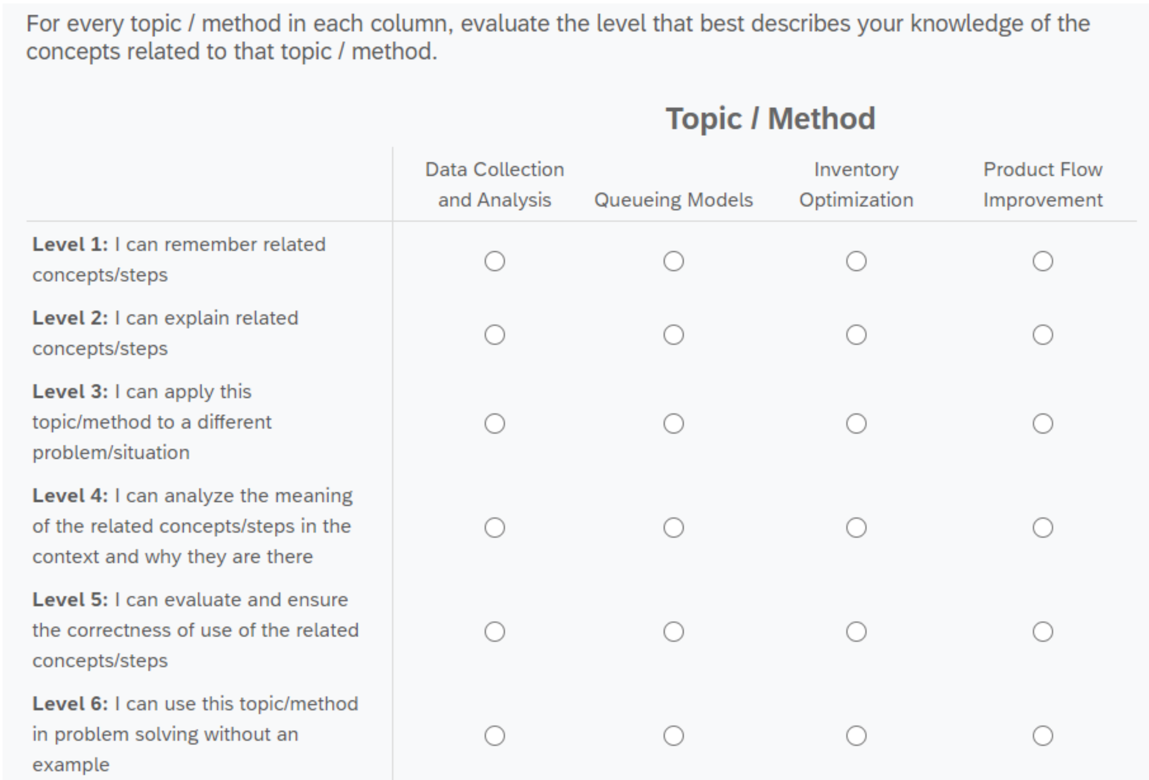
With regards to the Engineering Identity questionnaire completed at the start of the course sequence, the results of the independent t-test indicate there was no statistically significant difference between the participant's responses in the control and intervention group, at an alpha level of 0.05. This indicates that the participants on the control and intervention groups, on average, were not significantly different. When looking at the Engineering Identity questionnaires completed at the end of the operations research course (two semesters after the first one), the results indicate an increase for both groups. The results of the paired t-test indicate that participants in the control group ($M=8.16$, $SD=7.95$, $p\text{-value}<0.001$) and in the intervention group ($M=5.64$, $SD=6.65$, $p\text{-value}<0.001$) reported a statistically significant increase in Engineering Identity. However, the results of an independent t-test indicate this increase was not statistically significantly different between the groups. The results indicate a similar trend for all the elements of the Engineering Identity questionnaire except for the element of Interest, in which the control group showed a larger increased ($p\text{-value}=0.02$).

While it was hypothesized that the intervention group would have reported a larger increase in Engineering Identity, due to the CLICK approach, unfortunately, the research team was not able to control for the effects of the COVID-19 pandemic on the intervention group. COVID-19 forced academic institutions to suddenly switch to remote learning and because of that, the teaching delivery mode for the intervention group was remote while the control group did not experience this delivery mode in Fall 2019. Previous studies indicate that due to the inherent challenges and limitations of communication channels and transactional distance of online learning environments, students in these environments can struggle to create an identity [50], [51]. Hence, one would expect to see a decrease in the motivation as well as Engineering Identity scores in the intervention group due to the remote learning delivery settings, but it was interesting to find that the differences between the groups were not statistically significant. In other words, it can be hypothesized that the CLICK approach helped maintain the motivation and Engineering Identity scores to the level that was seen with the control group who were taught via face-to-face traditional teaching.

Self-assessment using Bloom's Revised Taxonomy and Students' Grades

The intervention group also completed a self-assessment instrument after submitting the assignment of the 3D simulation. The instrument is based on Bloom's revised taxonomy and it allows the students to rate their knowledge on six levels (level 6 is the highest). Figure 3 shows the self-assessment instrument with the concepts.

On average, students reported a score of 4.12/6 on their self-assessment ($Mdn=4$, $SD=4.14$, Range=[1-6]). Similarly, on average, students received an 81.76/100 on their grade for the assignment ($Mdn=81$, $SD=10.48$, Range=[56-98]). The assignments were graded using a rubric created by the course instructor. The results show that student grades were positively correlated with their reported self-assessment ($\rho=0.55$, $p\text{-value}=0.022$). This indicates that students were to correctly assess their knowledge and understanding of the concept covered in the 3D simulation assignment. The grade of students was also positively correlated with their IMMS responses (ρ=0.59, p-value=0.013) and their Engineering Identity responses at the end of the course (ρ=0.62, p-value=0.008). Thus, students with higher understanding reported higher motivation (measured by the IMMS) and higher Engineering Identity.



For every topic / method in each column, evaluate the level that best describes your knowledge of the concepts related to that topic / method.

	Topic / Method			
	Data Collection and Analysis	Queueing Models	Inventory Optimization	Product Flow Improvement
Level 1: I can remember related concepts/steps	○	○	○	○
Level 2: I can explain related concepts/steps	○	○	○	○
Level 3: I can apply this topic/method to a different problem/situation	○	○	○	○
Level 4: I can analyze the meaning of the related concepts/steps in the context and why they are there	○	○	○	○
Level 5: I can evaluate and ensure the correctness of use of the related concepts/steps	○	○	○	○
Level 6: I can use this topic/method in problem solving without an example	○	○	○	○

Figure 3. Self-assessment Bloom's revised taxonomy instrument

4. Conclusions, Limitations, and Future Works

This work presents the results of investigating the effectiveness of the CLICK approach on students' learning, motivation, and engineering identity in a second course in operations research. To achieve this, a 3D simulation learning module was developed to cover queueing theory and inventory control as well as process improvement concepts. The 3D simulation learning module was used in a second course of operations research in the IE at Penn State Behrend. The results of this investigation showed that there was no statistically significant difference between the control and intervention groups concerning motivation (as measured by the IMMS) and Engineering Identity. Nevertheless, the authors believe that maintaining students' motivation and Engineering Identity levels to the levels achieved by traditional face-to-face learning was an interesting outcome since remote learning usually comes with challenges that negatively impact students' motivation and identity. The self-assessment and students' grades showed a good level of understanding of the concepts. The students' self-assessment and grades were positively correlated which indicated that the students had correctly assessed their knowledge. The grades were positively correlated to the students' motivation as well as their Engineering Identity.

This work is part of an ongoing investigation of the effectiveness of the CLICK approach. The main limitation in this work resulted from the sudden shift to remote learning delivery mode due to COVID-19. The control group students were taught via face-to-face traditional teaching mode while the intervention group students were taught via the remote learning delivery mode. The researchers developed 3D simulation learning modules instead of VR modules to increase the scalability and allow all the students to have access to the learning module since the simulation software can be run on a regular computer compared to VR that requires specialized VR headsets and gaming-ready computers. Hence, this resulted in many confounding factors that the researchers could not control for.

Future work will include adding more concepts to the learning module. The module will be used in a simulation course where the students will be building a simulation model for the system after observing and collecting data from the learning module. The simulation model provided with the learning module will act as a virtual system in place of the real-life system. Students will also build alternatives to the current system to improve the system's key performance measures. In addition, more data will be collected in the future course. This data will help in analyzing the effectiveness of the CLICK approach across several courses in the IE curriculum. The usability of the learning modules will also be revised based on the students' feedback.

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