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IMMERSIVE SIMULATION-BASED LEARNING (ISBL): EFFICACY AND EFFECT OF NAVIGATION IN THE VIRTUAL ENVIRONMENT

A Thesis in

Data Analytics

by

Mahgol Nowparvar

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The thesis of Mahgol Nowparvar was reviewed and approved by the following:

Ashkan Negahban
Assistant Professor of Engineering Management
Thesis Advisor

Parhum Delgoshaei
Assistant Teaching Professor of Systems Engineering

Robin Guanghua Qiu
Professor-in-Charge, Master of Science in Information Science
Professor of Information Science

Colin J. Neill
Director of Engineering Programs
Professor-in-Charge, Data Analytics
Professor of Software and Systems Engineering

ABSTRACT

Problem-/project-based learning (PBL) is a well-established pedagogical approach that allows students to learn by solving complex real-world problems. There is a wide range of studies on the effectiveness of PBL for various learner groups across different disciplines. Moreover, there is a growing interest in using immersive technologies such as virtual reality (VR) in education. Immersive technologies provide a virtual/simulated learning environment that mimics real-world problems. These technologies provide risk-free learning environments that also facilitate remote learning. A combination of virtual learning environments and PBL enables the benefits of both concepts and further improves students' problem-solving skills, active-learning, and critical thinking. In the research presented here, bibliometric analysis and literature review of relevant papers published in the proceedings of previous American Society for Engineering Education (ASEE) annual conferences are used to investigate: (1) *where (in what disciplines/subjects) PBL and VR have been used together in engineering education?* And, (2) *how are VR and PBL integrated and used in engineering education?* Our findings suggest that there is a lack of formal assessment for the efficacy of virtual learning environments, which we aim to address in our analysis of ISBL effectiveness.

In the second part of this research, we introduce and evaluate the effectiveness of the Immersive simulation-based learning (ISBL) modules in an undergraduate engineering economy course. ISBL aims to combine the benefits of PBL and virtual learning environments and provides technology-enhanced problem-based learning, where the problem context is represented via a three-dimensional (3D) animated discrete-event simulation model that resembles a real-world environment. In a set of controlled experiments, students are randomly assigned into two different groups: Control and Intervention. Students in the intervention group use ISBL modules as part of their assignments, while the control group completes a set of traditional textbook problems. Well-established survey instruments help us collect data from students' demographics, personality, prior

preparation, motivation, experiential learning, engineering identity, and self-assessment of learning objectives based on Bloom's taxonomy. The results from our statistical analysis suggest that ISBL enhances certain learning outcomes related to motivation and experiential learning. We also provide a qualitative assessment of the proposed intervention based on detailed, one-on-one user testing and evaluation interviews.

In the third component of this research, we implement a set of ISBL modules in a computer science course to understand the relationship between the user's interaction and navigation in a virtual/simulated environment and their learning outcomes. The students are also asked to record their screens while navigating through the simulation environment. Our research team develop a video analytics tool via a machine learning algorithm to extract interaction's data from students' screen recorded videos, namely total time spent in the virtual/simulated environment, a modified standard deviation, and flag rate. We use the data collected from the surveys perform multivariable stepwise regression analysis to assess if/how the navigation related variables are predictors of the students' learning outcomes.

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Chapter 1

Introduction

Problem-/project-based learning (PBL) is a student-centered teaching and learning approach that enable students to learn through solving complex real-world problems. PBL motivates students to engage in the learning process, build strong critical thinking skills, and apply what they learned to solve real-world problems [1][2].

Immersive technologies including virtual reality (VR) presents an interactive and hands-on environment that increase students' engagements in learning activities [3]. These technologies offer an accessible, adaptable, and risk-free remote learning environment. The use of the combination of PBL and VR motivates students to be more engaging, improve their communication and problem-solving skills.

Immersive simulation-based learning (ISBL) offers an alternative teaching and learning approach that involves technology-enhanced PBL where the problem context is represented via a three-dimensional (3D), animated discrete-event simulation model that mimics a real user problem that students may face in their future career. The simulation is intended to help with contextualizing and visualizing the problem setting, allowing students to navigate through the virtual environment to observe and understand the underlying dynamics, collect data, and apply what they learned into solving real-world problems [4].

This thesis is done as part of an overarching research project that is summarized in Figure 1. Our research team build a simulation model of a real system to resemble real-world environment and develop a set of problems/projects activities around that simulation model. The simulation model and the PBL activities are what we call them ISBL modules. Moreover, the ISBL modules are implemented in various STEM courses at the Pennsylvania State University. The survey instruments and video analytics tool are then utilized to collect data from students. In this thesis, we use the data collected from the students to assess the effectiveness of ISBL in STEM education. The collected data are also used to assess the impact of navigation in the simulated environment on learning outcomes.

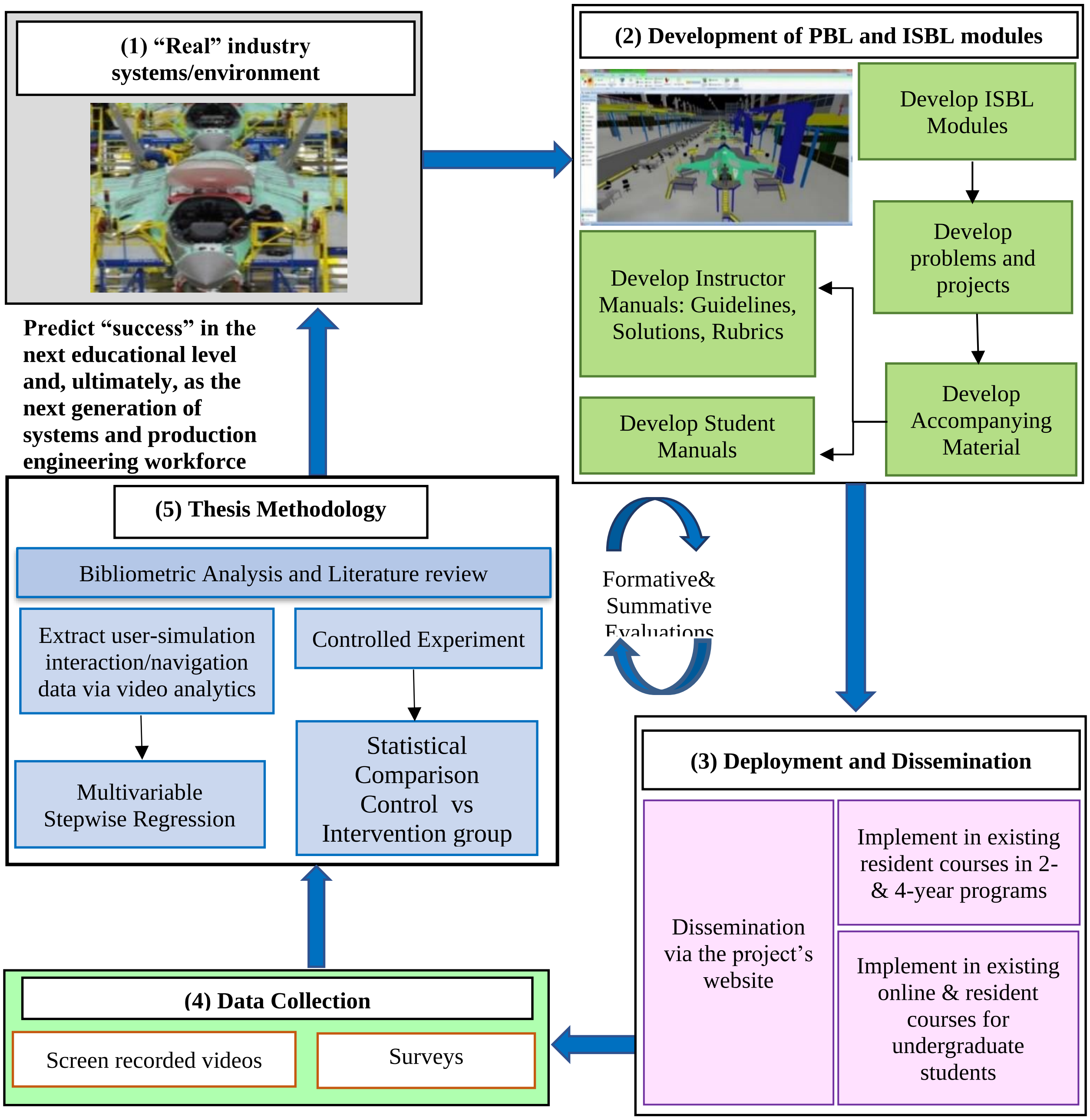

Figure 1. General design of overarching project

This thesis combines three research papers that form the subsequent chapters.

Chapter 2: Combining Immersive Technologies and Problem-Based Learning in Engineering Education: Bibliometric Analysis and Literature Review [5].

Chapter 3: An assessment of the effectiveness of ISBL modules for teaching and learning engineering economy concepts [4].

Chapter 4: Quantification and Impact of Learner Navigation in Immersive Simulation Environments [6].

Chapter 2 provides an overview of the bibliometric analysis and literature review to show *where* and *how* VR and PBL have been applied in engineering education. We perform bibliometric analysis of the relevant papers published in the proceedings of the American Society of Engineering Education (ASEE) annual conferences from 1996 to 2020. The bibliometric analysis is used to show in what engineering discipline PBL and VR are applied together. We then perform a literature review to highlight how the combination of PBL and VR have been integrated together in engineering education. We also analyze the trends related to PBL and VR application in engineering education over time and identify the research gaps [5].

In chapter 3, We propose and assess the effectiveness of ISBL modules in an undergraduate engineering economy course. In this experiment, students are randomly assigned to two different groups: an Intervention group that uses ISBL module as part of their assignments, and a Control group that completes a set of traditional textbook problems. Well-established survey instruments are utilized to collect data from students' demographics, personality, motivation, experiential learning, engineering identity, and self-assessment based on bloom's taxonomy of learning objectives. We use the data collected from the students to compare the two groups via statistical hypothesis testing. We also provide a qualitative assessment from the interviews conducted with student volunteers from the class [4].

Chapter 4 provides an assessment of the impact of user's navigation in immersive simulation environments. We implement a set of ISBL modules in a Computer Science course. In this experiment, students need to navigate through the virtual/simulated environment and record their screens as part of their assignment. We use a video analytics tool developed by our research team to extract interactions data from students' screen recorded videos, namely total time spent in the virtual/simulated environment, a modified measure of deviation from appropriate time allocations among different areas within the virtual environment (standard deviation), and percentage of unrecognized frames in a video (Flag Rate). We then perform multivariable stepwise regression analysis to determine if/how navigation-related measures can be predictors of learning outcomes [6].

Lastly, Chapter 5 summarizes the main findings of the three important topics of this project. First, we provide an overview of the bibliometric analysis and literature review results together with relevant future extensions. We then provide the concluding results of our statistical comparison to assess the effectiveness of the ISBL modules on students' learning outcomes. Furthermore, we provide the results and predictive models for our multivariable regression analysis. And, we discuss possible directions for future investigations.

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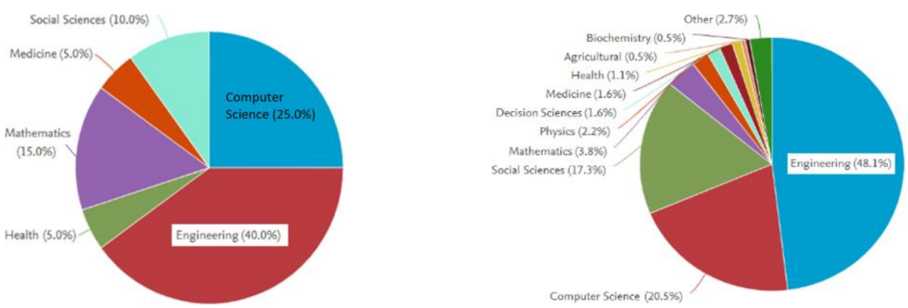
Chapter 2

Combining Immersive Technologies and Problem-Based Learning in Engineering Education: Bibliometric Analysis and Literature Review

2.1 Introduction

Problem-/project-based learning (PBL) is a form of student-centered active-learning approach in which students learn by solving complex problems that resemble those encountered in the real world. After decades of evolution, PBL has grown into an extensive teaching and learning method in a wide range of disciplines, including engineering education. Current studies show that students find PBL more engaging and effective, as they actively apply the information learned in the classroom to tackle real-life problems [1].

Immersive technologies, including virtual reality (VR), augmented reality (AR), and mixed reality (MR), use computerized environments and objects to simulate a "real" user experience [2]. There is a wide range of research on the effectiveness of immersive technologies in education. For example, several papers suggest immersive technologies to enhance specific learning outcomes in engineering by enabling remote/online teaching and providing a flexible and safe virtual environment [3]. Furthermore, immersive technologies can facilitate teaching and learning of design concepts (e.g., 3-dimensional design for a new product) while enhancing students' interactions, creativity, and spatial skills [3].



(a) Discipline breakdown for PBL. (b) Discipline breakdown for VR.

Figure 2. 1. Search results for PBL and VR in the Scopus bibliography database.

The use of immersive technologies in the context of PBL can potentially enable the advantages of both paradigms and further improve critical thinking and problem-solving skills, encourage effective communication and enhance students' motivation and learning experience. Motivated by the above and the fact that engineering is one of the main application areas for both PBL and VR (Figure 2.1), the objectives of this paper are to:

1) Use bibliometric analysis to show where (in what engineering disciplines/subjects) PBL and VR have been applied.

2) Provide a literature review to assess and understand how VR has been used in a PBL setting in engineering education.

The remainder of the paper is organized as follows. We first provide a brief overview of the bibliometric analysis technique. We then present the main results of our bibliometric analysis along with the observed trends over time in the use of PBL and VR. We then narrow down our focus and provide a summary and qualitative assessment of only those papers that discuss the use of VR in a PBL setting (i.e., integrated use of both tools). Finally, we present the conclusions and potential future opportunities. Figure 2.2 summarizes the general process used in this paper.

2.2 Bibliometric analysis: Where PBL and VR are used in engineering education

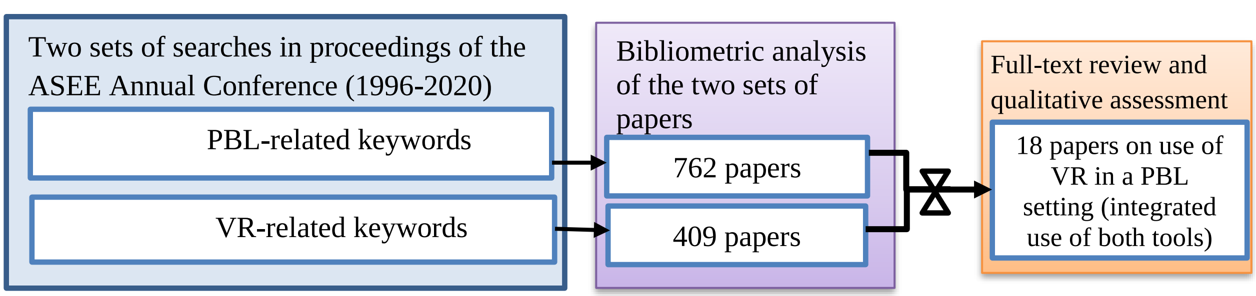
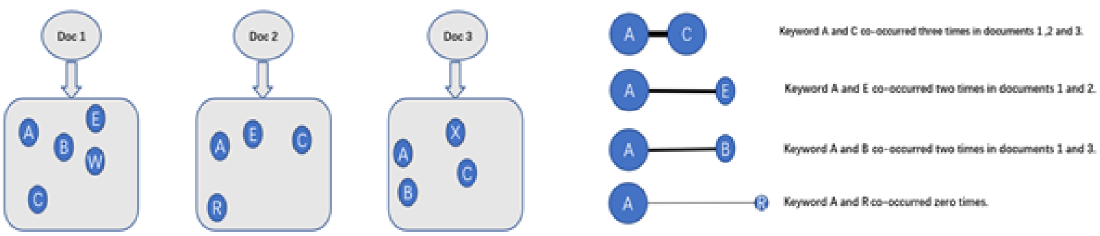


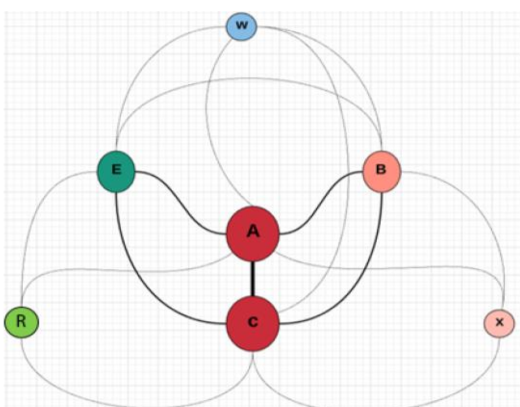
Figure 2.2. The general review process followed in this paper

Bibliometric analysis involves statistical techniques that can be used to analyze a scientific field by its publications and their characteristics [4]. Here, we use the Vosviewer tool to perform a bibliometric analysis of the proceedings of the American Society for Engineering Education (ASEE) annual conferences over a 25-year period from 1996 to 2020 collected via Scopus searches in their title, abstract, and keywords, using various search phrases related to PBL and VR. Our bibliography search using the phrases "problem-based learning", "project-based learning", and “PBL” led to 762 papers. Similarly, 409 papers are identified using “virtual reality” and “VR” as search phrases. An example of the complete Scopus search expression is:

TITLE-ABS-KEY (("Problem-based learning" OR "Project-Based Learning" OR “PBL”)) AND (LIMIT-TO (EXACTSRCTITLE , "ASEE Annual Conference and Exposition Conference Proceedings") OR LIMIT-TO (EXACTSRCTITLE , "ASEE Annual Conference Proceedings")) Next, we perform co-occurrence analysis [5]–[7] to classify and map co-occurred words and phrases among the collected papers related to PBL and VR to describe research trends. Figure 2.3 presents an illustrative example of co-occurrence analysis with three hypothetical documents (Doc 1-3) and the resulting map/network of keywords/phrases (denoted by A, B, C, E, R, W, X).



(a) The three documents and their keywords used in the example of co-occurrence analysis.



The size of nodes and length of links reflect the number of co-occurrences.

- A and C have the most co-occurrences and strongest connection.

- B and E co-occurred twice.

All keywords from the same document with only one co-occurrence:

- Have at least one link to each other

- Form clusters around the center

- Remain farthest from the center

- Form clusters around the center

- Remain farthest from the center

(b) The co-occurrence map/network of keywords in the three documents in Figure 3(a).

Figure 2.3. An illustrative example of co-occurrence analysis.

2.3 Results of the co-occurrence analysis

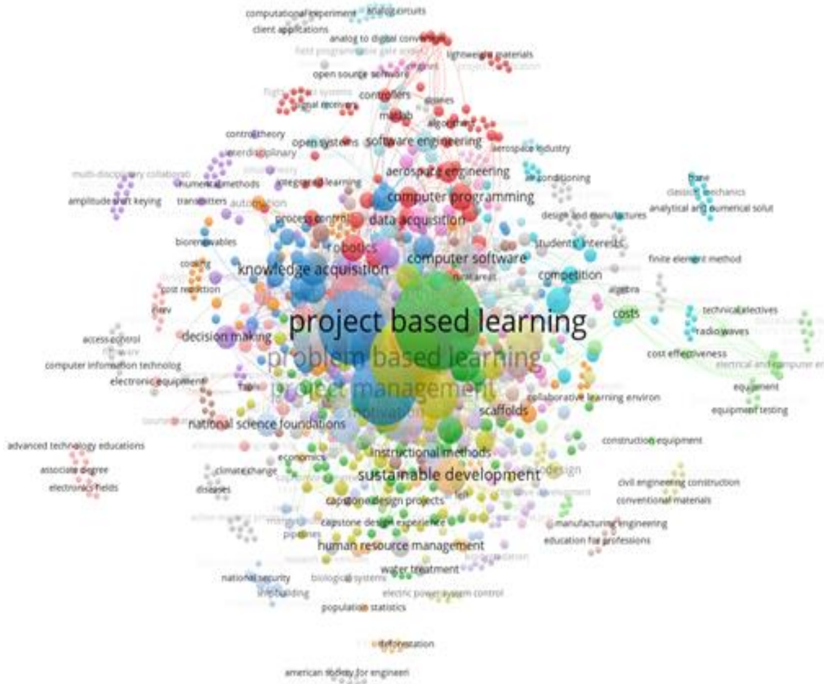
Figure 2.4 shows the co-occurrence map of keywords in the two sets of publications related to PBL and VR considered in this paper. The two maps help us identify clusters of keywords that cooccurred, which are then used to extract the related topic and engineering discipline as summarized in Table 2.1 for PBL and in Table 2.2 for VR along with a list of sample references.

Table 2. 1. Engineering discipline and topics derived from the co-occurrence map for PBL.

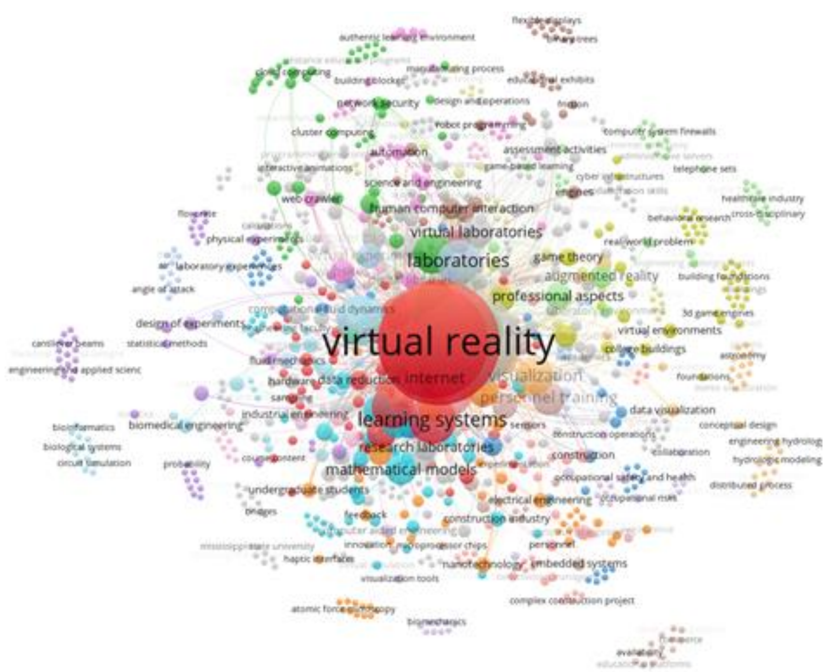
Discipline/Field	Keywords/Topics	Sample Papers
Electrical Engineering	Electrical equipment, Analog electronics and transistor, Electric system, frequency devices, Electronics technology program	[8]–[15]
Mechanical Engineering	Machine concepts, Finite element analysis, HVAC, Fluid and Thermal design, Thermodynamics, Dynamic	[16]–[22]
Aerospace Engineering	Aerospace research materials	[23]
Computer Engineering	Concepts of CE (generic)	[24]
Biosystem Engineering	Biosystem engineering concepts (generic)	[25]

Table 2.2. Engineering discipline and topics derived from the co-occurrence map for VR.

Discipline/Field	Keywords/Topics	Sample Paper
General Engineering	Mathematical models, Probability and statistics, Engineering design education, Laboratory accident training, medical care technology, Community health, Building environment, Web-based learning, Simulation, Visualization	[2],[26]–[33]
Computer Engineering	CE technology, VR Development, Computer game application, Mobile robot simulations, Game training environment, Engineering design	[34]–[36]
Mechanical Engineering	Wind tunnels, Prototype vehicles, Robot system, physical experiment, Virtual dynamic laboratory, Uncertainty analysis	[37]–[39]
Electrical Engineering	Nanotechnology, VR simulation	[40]
Biomedical Engineering	Simulations in biosystems	[41]

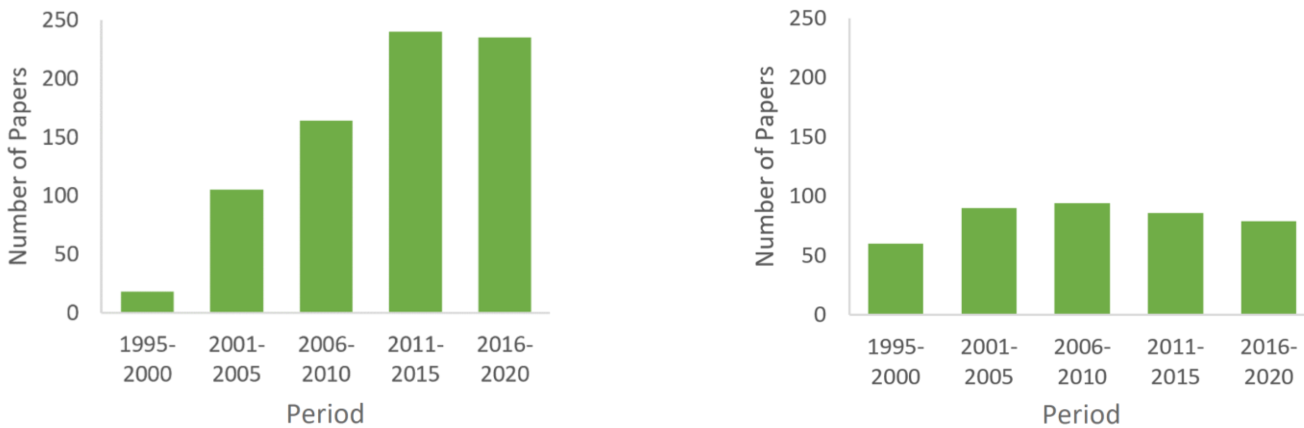


(a) Project-based learning



(b) Virtual Reality

Figure 2.4. The co-occurrence network for the two sets of papers related to PBL and VR.



(a) Problem-based learning (PBL)

(b) Virtual Reality(VR)

Figure 2.5. Trend analysis for PBL and VR.

Figure 2.5 presents the trends in the use of PBL and VR in engineering education measured by the number of papers published on the corresponding topic in the proceedings of ASEE annual conferences. We observe a clear increasing trend in the use of PBL over the years. However, we observe an initial uptick trend in the use of VR in the early 2000s after which the trend seems to have leveled out. By comparing Figures 2.5(a) and 2.5(b), we can see that PBL is used much more frequently than VR in engineering education. This is expected as PBL has been around for much longer and is well-established in educational settings with a more cohesive body of research, empirical evidence, and theoretical support in comparison to VR.

2.4 Literature review: How PBL and VR are integrated in engineering education

This section aims to provide a review of papers published in the proceedings of ASEE annual conferences to highlight how PBL and VR have been integrated and used together in engineering education. Through full-text review of the original 409 papers returned by our keyword search related to VR, 18 papers are selected that use a combination of PBL and VR, which are summarized in the following subsections. We divide the reviewed papers into the following groups based on the engineering discipline they belong to: Computer Engineering and

Information Sciences, Mechanical Engineering, Electrical Engineering, Biomedical Engineering, Geotechnical Engineering and Environmental Engineering, and Industrial and Manufacturing Engineering. If a paper belongs to multiple disciplines or does not neatly fall under a single category, then it is included under “General Engineering”. At the end of this section, we discuss the main findings and insights derived from our literature review.

General engineering

In [26], the author employs a combination of formal and informal learning using immersive technologies and PBL for interdisciplinary teams consisting of engineering and nursing students. The team project involves developing healthcare-related apps that patients can use on their smartphones, including apps that use immersive technologies (e.g., for cognition and memory health). The main goal of the study is to expose STEM and non-STEM students to various fields, such as health care, virtual reality, and social and community issues and understand how interdisciplinary instruction affects students’ ability to identify, formulate, and solve problems, communicate effectively, appreciate the impact of planning and engineering solutions, and develop understanding of ethics-related factors. The effectiveness of integration of PBL and immersive technologies is measured with pre/post surveys related to the above outcomes and the results indicate increased technical and collaborative skills in students.

The authors in [42] work with graduate and undergraduate students to develop a web-based 3D visualization and cluster computing system for disaster data management, resource distribution and communication between local authorities and disadvantaged populations affected by a disaster. The developed tool can be used on Google Earth-enabled mobile and desktop devices as well as a Cave Automatic Virtual Environment (CAVE). More than 30 graduate and undergraduate students participated in the research and hands-on experiences involving PBL and VR in order to develop the web-based disaster management and communication system. The authors mention that three graduate students completed their master’s thesis based on this project, and more than 10 undergraduate students completed their senior design project based on this research. However, they do not provide any additional assessment data related to the impact of PBL-VR integration on student learning or motivation.

The work in [43] develops a prototype of a multi-dimensional Desktop Virtual Reality (dVR) framework to help students organize, present, and visualize engineering and technological literature (as an alternative to reading textual information). The literature is represented as geometry objects embedded in a graphic interface where users can navigate within the 3D environment, view the literature from multiple perspectives, and interact with the virtual environment by sorting and re-structuring the visualized literature. The authors discuss the extension and application of the dVR prototype in PBL exercises, for example, an IT project involving generation of a taxonomy to classify operating systems or programming languages for a Computer Information Technology course. However, no assessment results are reported on the effectiveness of PBL-based exercises enabled by the proposed dVR environment.

Computer engineering and information sciences

In [44] , the authors propose novel immersive simulation-based learning (ISBL) modules for teaching and learning database concepts. The proposed modules include a three-dimensional, VR-compatible simulated environment with PBL activities defined around the virtual environment to mimic a real-world situation where the student is hired as an intern to design a database for a hypothetical company/system. Students observe the simulation as it is running and are asked to create an entity-relationship (ER) diagram and relational schema by identifying relevant entity types, their relationships, and attributes. As part of the assessments, students are divided into two groups. The “intervention group” uses the ISBL module, while the “control group” is assigned to an equivalent PBL assignment without the accompanying immersive simulation. The authors collect data on demographics, motivation, usability, and students’ grades in pre/post quizzes. The results confirm the effectiveness of the proposed modules with potential improvements in certain constructs related to motivation.

The work in [45] proposes a PBL-based approach wherein an interactive VR framework is used for delivering instructional materials to the students in an introductory computer animation course. The framework includes a VR laboratory capable of delivering conceptual and practical training and extensible VR modules designed to support immersion, navigation, and interaction. However, this is a work in progress paper and does not discuss any formal assessment results on the effectiveness the proposed PBL-VR integration.

The authors in [46] develop an advanced learning lab equipped with tablet PCs, wireless slates, and a SMART interactive whiteboard as an educational infrastructure to promote problem-based learning, collaborative learning, and assessment. A supplementary VR learning platform is also discussed for enhancing student learning outcomes by converting abstract concepts into vivid animations and providing game-like interactivities, and by making the learning experience fun while still retaining the underlying content. The authors report that the lab and support VR platform are at the initial implementation and testing phase, hence no quantitative assessment data are provided, but they lay out future assessment plans involving both formative and summative evaluations in a data structures course and an object-oriented design and analysis class.

Mechanical engineering

The authors in [47] develop, implement, and test two immersive prototype applications called AR-Skope and VR- Skope to support collaboration among Architecture, Construction, and Mechanical Engineering students. The prototype integrates AR and VR with Building Information Modeling (BIM), visual simulations, and interactive lessons. One course from each of the three participating disciplines is selected for implementation. Students are divided into four different groups to complete a project that involves physically visiting a campus building and a walk-through using VR and AR Skope (like having an interactive x-ray vision) to explore its various components such as the façade system, structure, mechanical systems, plumbing, etc. Pre/post attitude surveys, technical reports, videos and interviews are used to assess the effectiveness of the integration of VR and AR in interdisciplinary projects. The results suggest that the proposed method can effectively decrease students' negative attitudes toward collaborative learning and improve interdisciplinary team interactions.

In an effort to improve student learning and engagement, the authors in [48] develop and integrate an interactive virtual laboratory in a pneumatics and hydraulics systems course designed based on a PBL pedagogical model. The framework allows students to compare virtual experimentation using Automation Studio software with physical real-world experiments in a traditional lab setting.

Preliminary assessment results from student skills in pre-lab preparation, lab report grades, and a survey indicate that incorporating virtual experiments in conjunction with physical experiments in a PBL setting is advantageous to student preparedness and understanding of the course material.

In an early paper [49], the authors develop an interactive virtual environment using the LabView software to support both inquiry-based and project-based learning in a Thermal Systems Laboratory course. Traditionally, the course involves equipment-intensive experiments where students are given detailed and rigid procedures to follow, creating a passive learning environment and suppressing students' motivation. The virtual environment aims to address these issues and overcome cost, safety, and other limitations of the physical lab. The PBL activities in the virtual environment involve designing instruments and data acquisition systems. However, the paper does not present any assessment results related to the effectiveness of the virtual lab.

Electrical engineering

The authors in [50] propose a set of interactive simulations and virtual experiments intended to facilitate "learning-by-doing" and PBL in fiber optics, photonics, and telecom courses and for onsite, online, and hybrid delivery methods. For example, in the simulation, learners can explore the procedure of switching or handing off a mobile phone from one cell to another as it moves across cell boundaries in a system of different sized cells. The student can also change the parameters (e.g., probability of blocking, traffic intensity, and number of users) and see their effect on the simulated system. However, no assessment data are reported on the effectiveness of the simulations and virtual experiments.

Biomedical engineering

In [51], besides traditional teaching and learning methods, and laboratory activities, the author presents case-based and problem-based learning using browser-readable interactive 2D and 3D objects, animation, videos, 3D objects of real components, and 3D internal and external human body virtual tours, that the students can study. According to our reviewers, learners and assessors, this an effective method for problem solving and assessment in biomedical engineering because it forces both the student as well as the tutor to focus, create new wealth, and encourage outcome-oriented educational practices. However, no formal assessment experiments are discussed.

Geotechnical and environmental engineering

The work in [52] studies the use of VR for teaching Concentrating Solar Power (CSP) technology. A scale model of an actual alternative energy research facility in Louisiana is developed in the CAD software and imported into a VR game engine with interactive educational activities placed throughout the VR environment and students complete them to virtually produce solar power. The VR environment is then used in conjunction with PBL, where students are presented with a problem, that is, to start up the (virtual) CSP plant in order to produce the needed solar power. Pre/post-tests and a questionnaire are administered for college and high school students. The assessment results show a substantial improvement on the post-tests as well as positive feedback about the VR experience, exploration, collaboration, and interaction combined with PBL as an effective educational method.

The game-based module for geotechnical engineering students in [53] develops a mixed-reality and mobile game-based learning environment called "GeoExplorer" that supports PBL and experiential learning, and enables students to experience field testing to design and assess a particular site's flood-protection levee. Students are assigned to games related to cone penetration tests and levee design and assessment capabilities after attending lectures. As part of the assessments, pre/post surveys are administered, which contain the same technical questions as well as additional questions designed to assess the game quality and students' perception of its effectiveness. The results indicate students' positive attitude towards the VR-PBL integration with over 90% of participants perceiving this to be an effective way to implement class learning in practice. There was also a 20% improvement in students' understanding of the material measured by their scores on the technical questions.

The authors in [54] combine PBL and VR in wind/green energy education by assigning students to projects that involve designing and testing different components (such as wind turbine blades) using 3D modeling software, including SolidWorks and Unity. Preliminary assessments suggest students can effectively complete the design tasks in a virtual setting and the feedback received from the students was mainly positive, especially with regard to exposure to the green product topic surrounding materials, fabrication, testing, and measurements.

In another paper related to green energy[55] , a VR learning environment and laboratory is developed using the VRLE platform and SolidWorks to support project-based learning and improve students' learning related to Proton Exchange Member (PEM) fuel cells. During VR simulation, students can vary the fluid parameters and explore the changes in current and voltage, perfectly mimicking the physical laboratory activity. Assessments are yet to be conducted to establish the effectiveness of these VR learning modules of PEM fuel cells.

The work in [56] deliver interactive GIS instructional material using an immersive CAVE-based technology named iSpace and a low-cost desktop VR (dVR). While the dVR lacks the high fidelity and immersion of CAVE, it addresses accessibility and affordability issues. A three-tiered framework is used including a concept model for GIS instruction, mapping component, and customization for mode-specific delivery of design materials. The framework enables PBL, experiential learning, and active learning in the context of VR. However, this is a work-in-progress paper and does not report any assessment data.

Industrial and manufacturing engineering

In [57], the authors introduce an interactive VR, PBL and case-based learning environment to support student collaboration and problem-solving related to Failure Risk Analysis. The goal is to for students to work on open-ended, interdisciplinary problems and interact with real-life challenges, where students can learn by doing in an interactive 3D multimedia environment. For example, students can disassemble and then re-assemble 360-degree panoramic and 3D VR interactive objects by virtually going to factories, R&D studios, and laboratories. In addition, spreadsheets and video are used as part of the integrated PBL-VR modules. This work has been ongoing for several years, and several universities and companies have adopted the technology, however, the paper does not provide any formal assessments on its effectiveness.

The authors in [58] develop a set of VR models, PBL, and case studies to be integrated with various courses in the industrial engineering curriculum and help address competency gaps in manufacturing workforce. Student teams are assigned to work on industry-based projects that require VR walk-through tours enabled by a discrete-event simulation model of an actual Boeing manufacturing line. A formal rubric is used for scoring the projects as recommended by the “Field-Tested Learning Assessment Guide”, classifying the assessment based on the students’ learning outcomes such as knowledge, skills, or attitude. The results indicate that integrating VR and PBL can address students’ competency gaps by incorporating the knowledge and skills gained from various course lectures.

2.5 Discussion and qualitative assessment of the reviewed literature

This section discusses the main insights derived from our qualitative assessment of the papers included in our literature review.

- <u>*Increased attention to learning theories:*</u> While Figure 2.5(b) shows that the number of papers that discuss VR in engineering education seems to have plateaued in the last decade, the number of papers that integrate VR and PBL seems to be increasing according to Figure 2.6 with a clear uptick during the 2016-2020 period. This is an interesting an important finding as it can be an indication of a possible shift from *development* of computerized VR simulation environments to *designing meaningful immersive learning activities* that are supported by pedagogical and psychological theories enabled by PBL such as constructivism theory, self-determination theory, and information processing theory.

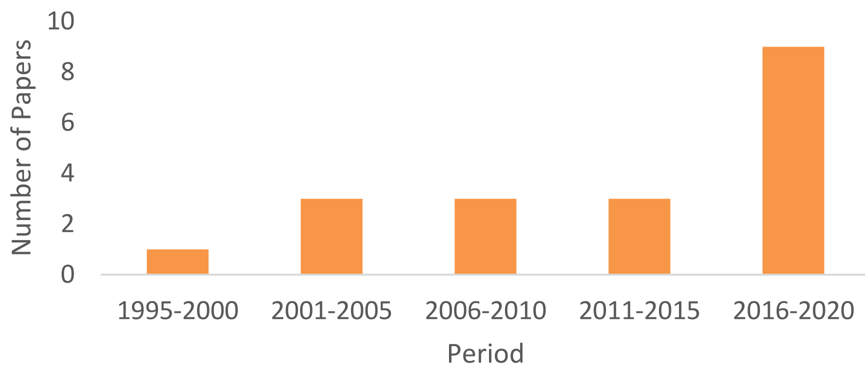


Figure 2.6. Trend analysis for the use of PBL in the context of or enabled by a VR environment.

• *Breadth of application domains:* The 18 articles included in our literature review cover seven engineering disciplines and several related subjects, indicating a broad interest in the integration of PBL and VR in engineering education. However, these applications are not uniformly distributed among engineering disciplines. For example, we see more examples of PBL-VR integration in geotechnical, environmental, and mechanical engineering.

• *Type of learning activity:* Our literature review reveals that VR has been integrated with both problem-based and project-based learning as the reviewed papers report different types of learning activities from small assignment-like modules to more complex, semester-long projects and case studies. We also see that PBL-VR integration is used for both individual activities and teamwork including interdisciplinary teams from different programs/courses. Therefore, it does not seem that integrating VR into PBL affects the team aspects and potential for collaborative and interdisciplinary learning.

• *Lack of formal assessments*: The most important gap in the reviewed papers is the lack of formal assessments of the effectiveness of PBL-VR integration. The majority of the reviewed papers discuss the technical details related to development of the VR environment and/or explore potential uses in a certain course or program, but do not perform assessments (e.g., controlled experiments) or report quantitative assessment data on the impact of their intervention on student learning, motivation, skill development, retention, and other important outcomes. However, the few studies that did perform assessments indicate improvements as a result of combining VR and PBL.

2.6 Conclusions, limitations, and future work

In this paper, we first perform a bibliometric analysis on the ASEE annual conference proceedings from 1996 to 2020 to identify the engineering disciplines and related topics where PBL and VR are used. Our trend analysis on the number of publications over the years shows an increase in the use of both PBL and VR and their integration in engineering education. The increased popularity of VR can be partly due to the increased availability and affordability of immersive technologies in recent years that have led to many engineering programs adopting VR technologies (e.g., in the form of virtual learning factories/laboratories) due to the flexible, cost-effective, and risk-free environment they offer (e.g., compared to physical laboratories that involve expensive and complex equipment).

We also perform a qualitative assessment of the studies that implement VR in conjunction with PBL across different engineering fields. Perhaps the most critical gap in the reviewed literature is related to lack of formal assessments as many papers report on developing a new and/or implementation of an existing immersive environment without providing rigorous evidence on the effectiveness and impact on student learning, motivation, and other outcomes. Far more attention needs to be given to assessments given the paucity of scientific evidence on the effectiveness of immersive technologies, and especially given the existence of mixed findings in some cases related to impact on students' motivation vs. learning and task performance (for example, see [59]).

Scalability (in terms of learners' access to VR equipment) and high development time/cost of VR learning environments are among the significant factors that affect the adoption and use of immersive technologies in education including engineering education. While there are several studies aim to reduce or eliminate such scalability barriers, we believe future research could focus more on these issues. For example, the immersive simulation-based learning (ISBL) method proposed in [44] supports both a “desktop mode” or “low-immersion mode” of use on a typical 2D display as well as a “VR mode” or “high-immersion mode” via a VR headset (if available) for an enhanced immersive experience. Moreover, by using a commercial discrete-event simulation software with 3D animation features and VR compatibility, the development time/cost of their ISBL modules is significantly less than the programming effort required to implement similar simulations in a VR platform such as Unity. Finally, we found a small number of studies that integrate artificial intelligence within immersive virtual environments. Design, development, and assessment of combined AI-VR learning environments is another rich area for future research.

We hope that this paper accelerates the discussions and ongoing research on PBL enabled by immersive virtual environments in engineering education. We plan to extend our literature analysis to encompass all STEM fields and other journals and conferences that publish educational research.

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Chapter 3

An Assessment of Simulation-Based Learning Modules in an Undergraduate Engineering Economy Course

3.1 Introduction and Background

The Immersive Simulation-Based Learning (ISBL) approach proposed in this paper aims to close the gap between learning and skills that the students attain during their education and the real-life problems they face and solve in their professional life. ISBL offers an alternative teaching and learning method that combines the benefits of immersive simulated environments and problem-based learning (PBL). ISBL is student-centered and aims to motivate students to formulate engineering problems and situations based on real-life context. This paper focuses on an implementation and assessment of ISBL for teaching and learning engineering economy. The interested reader is referred to [1] for another application of ISBL in a database design course.

Engineering economy is one of the fundamental courses in an engineering curriculum and one of the core engineering competencies covered in the Fundamentals in Engineering (FE) exam. The concepts learned in an engineering economy course aim to help engineers make informed and economical decisions in engineering settings [2]–[5]. The topics covered are useful to the students in their personal and professional life, providing many opportunities to incorporate real-life examples to enhance teaching and learning. Nevertheless, engineering economy is generally characterized as a course with a high failure rate, which is often attributed to engineering students' low engagement and motivation toward the topics covered in the course [6]. In addition, students usually struggle to apply what they have learned in class in actual engineering applications [6]. Through the proposed ISBL approach, we aim to improve students' motivation and engagement by providing a contextualized learning experience designed to enhance problem-solving skills.

PBL is a well-known student-centered approach that utilizes active learning where students solve complex problems that mimic problems encountered in real-life applications [7]. PBL has proved to improve innovation [8], metacognition [9], engagement and meaningfulness [10], [11]. In addition, it encourages design thinking [12] as well as curriculum integration [13], [14]. PBL helps students learn by applying the learned knowledge rather than memorizing it [15] and is recommended as an effective teaching and learning method in engineering economy courses [16].

On the other hand, simulated and immersive environments, such as virtual reality (VR), insert the user into a virtual world with which the user can interact [17]. Several studies have investigated the effectiveness of immersive technologies in engineering education [18]. Immersive technologies provide portable and risk-free learning environments that facilitate location-independent learning [18]. Moreover, these technologies are shown to enhance certain learning outcomes in engineering disciplines such as creativity and spatial skills [18]. The reader is referred to [19] for a comprehensive review of immersive virtual environments in higher education, and to [20] for a bibliometric analysis on the combination of PBL and immersive technologies in engineering education.

In this paper, we propose and investigate the effectiveness of ISBL as an alternative teaching and learning method that enables PBL in the context of an immersive simulated environment. In the following sections, we first describe the different components of ISBL, supporting pedagogical and psychological theories, as well as the sample ISBL modules used in our experiments related to an undergraduate engineering economy course. We then describe the experimental design and present the results of our quantitative assessments and statistical comparisons as well as a set of qualitative assessments based on user interviews. Finally, we will conclude the paper by discussing the lessons learned and future research opportunities.

3.2 Immersive Simulation-Based Learning (ISBL)

The proposed ISBL modules are specified by:

a) A *three-dimensional, VR-compatible discrete-event simulation model* that resembles a real system or environment. The simulation serves as the context and enables technology enhanced PBL. The simulation models used in the proposed ISBL modules can be explored in 2D on any typical display or via a VR headset for an enhanced immersive experience.
b) A set of *entities* in the simulation that can represent people, products, raw material, information/data that are processed, assembled, manufactured, stored, transferred, or transported depending on the context being simulated.
c) A set of *processes* in the simulated environment that represent the stages or stations that the entities go through during the simulation run.
d) A *learning activity* in the form of problem- or project-based learning defined around the simulated system. The learning activity is inspired by and resembles real-world situations that learners may face in a professional setting or future workplace.

Many of the pedagogical and psychological theories that support PBL also apply to ISBL or are augmented as a result of the integration with a virtual/simulated environment. For example:

- ISBL enables long-lasting development of critical thinking and problem-solving skills by: (a) activating relevant prior knowledge; (b) providing a contextually-enriched environment (via immersive simulations) that mimics future professional settings; and (c) encouraging learners to elaborate on their knowledge to solve a real-world inspired problem. These are the three principles of the *Information Processing Approach to Learning* theory [21].
- The immersive simulations in ISBL provide the context and an environment to interact with, which are often missing in STEM education. This enables knowledge to be constructed via interactions with the virtual environment and indexed by relevant contexts. This aligns with the *Constructivism Theory* [22], which suggests learners construct their interpretations of the real-world world through cognitive and interpretive activities and help construct mental models by accommodating new ideas/phenomena with prior knowledge.

- ISBL enables learners to consider their views and take greater responsibility for their learning. As a result, ISBL aligns with the *Self-determination Theory* [23] by promoting *autonomous* motivators, unlike traditional methods that are primarily based on *controlled* motivators such as rewards and punishments (e.g., passing or failing a test), which often lead to superficial learning and cause a sense of pressure and anxiety.
- ISBL is also suitable for professional and continuing education as it supports some of the main pillars of the *Adult Learning Theory* [24] by providing a self-directed and problem-centered learning experience that draws on previous work experiences and integrates into the professional learner's everyday life as ISBL problems/projects resemble real-world situation.

For the ISBL modules investigated in this paper, the immersive simulations are developed using the Simio® simulation software [25], which does not incur any technology fee for academic and classroom use and is compatible with VR, giving the learner the option to view the simulated environment on a 2D display (low-immersion mode) or via a VR headset (high-immersion mode). Students use virtual site visits (by navigating in the simulation) to make observations and collect any necessary data (as opposed to visiting a real-world facility in person). This helps eliminate several critical barriers in current STEM education and workforce development, namely: (a) geographical barriers that prohibit contextualized learning, e.g., lack of proximity to industries or geographically dispersed formal/informal learners in online education; (b) companies' reluctance to provide access to their facilities and data; and/or, (c) logistics/schedule constraints that prohibit real-world site visits (e.g., conflict with other classes or work commitments for professional students).

The following section describes the integration of several ISBL modules in an undergraduate engineering economy class that we used in our assessment experiments. For a list of ISBL modules developed for other STEM courses/disciplines, please see our project website at https://sites.psu.edu/immersivesimulationpbl.

3.3 ISBL Implementation in an Undergraduate Engineering Economy Course

The Industrial Engineering (IE) Department at Penn State University - The Behrend college offers an undergraduate introductory course in engineering economy. This is a required course for IE students and an elective course for other engineering and engineering technology majors. The course is offered in the fall and spring semesters. The high-level objectives of the course can be summarized as follows:

- Apply the theoretical and conceptual basics of financial analysis including time-value of money, cash flow diagrams, economic equivalence, present worth analysis, annual worth analysis, cost-benefit analysis, rate-of-return, depreciation, and income taxes.
- Make informed financial decisions when selecting among several viable alternative projects.
- Identify how engineering decisions during product design, process selection, manufacturing system design, etc. can affect a company's financial performance.
- Develop skills that extend the basic concepts needed to solve various problems encountered in professional and personal financial situations.

The class is structured to be taught online and includes video lectures, online assessment questions for each lecture, quizzes, homework assignments, and three exams. The course sections used in this study were offered in Fall 2020 and Spring 2021. Our experiment (as described in the following section) involved a “control” and an “intervention” group. Both groups used the same material offered by the same instructor and via the same delivery method. The only difference was the use of the ISBL learning module instead of traditional homework assignments for the intervention group.

Four ISBL modules are integrated into the course to mimic real-life systems and engineering economy problems. Students are given a week to complete each ISBL assignment following the lecture on the respective topic. The document that comes with each module includes a description of the system at hand and the engineering economy problem(s) to be solved. In each ISBL module, the students are given a role. For example, in one of the modules the student is "hired" as a consultant to help a restaurant compare different loan options and select the most economical alternative. Each module is also accompanied by a 3D, VR-compatible, animated simulation model that is to be treated as the "real-world system" under study. The ISBL modules used in our experiments are related to a restaurant, a manufacturing assembly plant, a warehouse, and an airport terminal. Figure 3.1 provides a screenshot of some of the simulated systems used in the ISBL modules.

Figure 3. 1.The simulation environments associated with the ISBL modules used in this paper.

For the sake of conciseness, we describe only one of the ISBL modules here and refer the interested reader to our project website at https://sites.psu.edu/immersivesimulationpbl where all ISBL modules developed as part of our ongoing project are shared publicly. The airport terminal has two areas with several self-check-in kiosks, a check-in counter, one ID/boarding pass check-point station, and two advanced imaging technology (AIT) stations for scanning passengers and their luggage. There are two gates in the boarding area at the terminal each having its own seating/waiting area, where passengers wait before boarding on their flight. Flights board and leave according to a stochastic process specified in the simulation model.

The engineering problem to be solved is as follows. The airport terminal plans to purchase and install vending machines near the gates to serve the passengers. Six candidate options have been identified that vary in terms of the number and type of vending machines to be installed, the number of choices (menu items), price, and quality of the drinks/snacks. Students are asked to treat the simulation as the "real" system and use virtual site visits to collect the data that they need to perform an economic analysis.

As for the learning objectives, after successful completion of the ISBL module, the student will be able to:

1. Collect data from the real-world system under study and estimate the cash flows needed for the economic analysis.
2. Compute the internal rate of return (IRR) for the investment options under consideration.
3. Perform rate of return (ROR) analysis to compare multiple alternatives and select the most economical option.
4. Perform present worth (PW) analysis to compare multiple alternatives and select the most economical option.
5. Verify the ROR and PW analyses by comparing the outcomes of the two methods.

3.4 Research and Experiment Design

Our study compares two groups of students: an "intervention" group that used ISBL modules as part of their assignments; and a "control" group that used traditional textbook problems as assignments. All other factors including the instructor, course syllabus/structure, instructional mode, textbook, etc. remain the same for both groups. Figure 3.2 summarizes the experiment process.

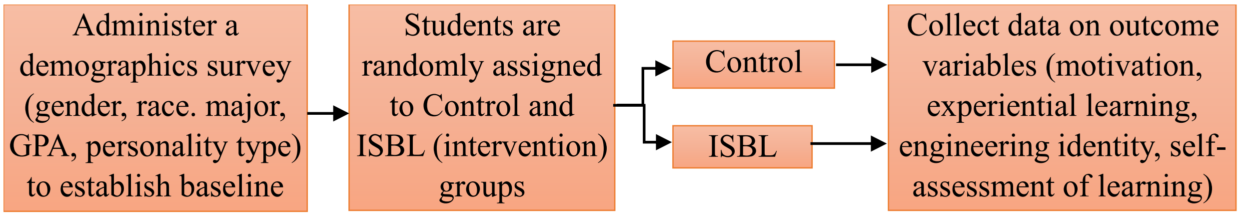


Figure 3.2. General design of the assessment experiments

We use the following instruments to collect data from research participants (all necessary IRB approvals are obtained prior to the experiment and data collection).

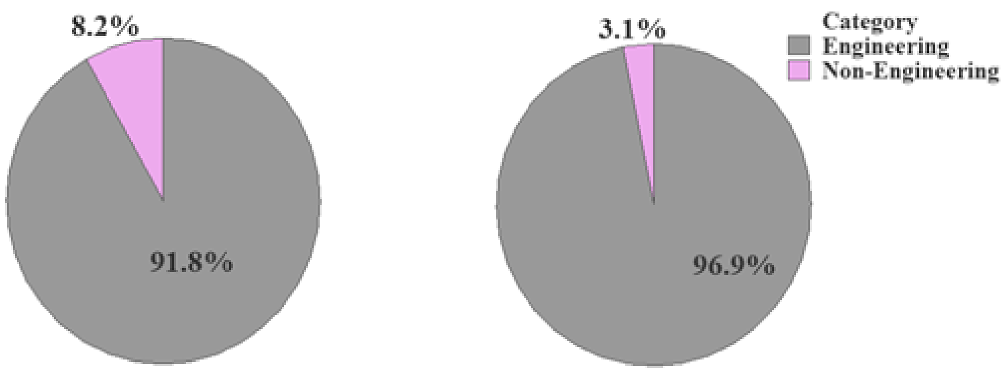
1. **Demographics survey:** The survey is used to collect data on gender, race, grade point average (GPA), major, semester standing, prior work experience, and personality type.
2. **Big Five Inventory (BFI-10) personality test:** The BFI survey questionnaire collects data about students' behavioral personalities and behavior across various situations [26]. The 10-item BFI measurement is developed to allow effective assessment of the five personality dimensions including Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness.
3. **Instructional Materials Motivation Scale (IMMS):** The IMMS [27] survey is used to assess the student's motivation. The survey consists of 12 Likert scale questions measuring attention, relevance, confidence, and satisfaction for students earning a degree in engineering.
4. **Experiential Learning Survey:** Experiential or experience-based learning generally refers to settings where students participate in activities that enable learning by doing. This instrument is a 12-item questionnaire that evaluates the student's perception of experience-based educational instruction as established in the experiential learning theory [27]. Here, we specifically focus on two of the constructs measured by this instrument, namely how the *environment* influenced learning, and how useful the learning experience was in terms of potential *utility* in future endeavors. It is worth noting that the original experiential learning instrument includes two other constructs, namely *active learning*, and *relevance*, which were excluded in our implementation of this instrument due to their overlap with the constructs measured by the other instruments that we used here. For example, *relevance* is

measured by the IMMS survey, and *active learning*, which refers to the student's level of engagement with the learning material, is directly related to "Attention" – also measured by IMMS.

5. **Engineering Identity Survey**: The engineering identity survey is created to understand students' career choices and interests in engineering fields [28]. The 10-item questionnaire is constructed to measure three constructs related to the student's: (a) perception of their performance and competency, i.e., ability to perform well in gaining engineering knowledge; (b) interest in the (engineering) subject; and (c) recognition, i.e., being acknowledged by their peers/instructors as a successful engineering student.
6. **Self-assessment based on Bloom's Taxonomy of learning objectives:** This self-assessment survey is designed to provide insights into students' self-perceived knowledge related to a set of topics/concepts [29]. In our study, students are asked to rank their knowledge of various engineering economy topics by selecting one of six levels adapted from Bloom's taxonomy that they think best describes their level of learning. For each topic, the six levels that the respondent can choose from are as follows: (1) I can *remember* related concepts/methods; (2) I can *explain* related concepts/methods; (3) I can *apply* this topic/method to a different problem/situation; (4) I can *analyze* the meaning of and justification for related concepts/methods; (5) I can *evaluate* and ensure the correct use of the related concepts/methods; (6) I can *create* new solutions by using this topic/method in other problem-solving situations without an example.
7. **Student interviews:** Interviews are conducted with student volunteers from the class to obtain a qualitative assessment of their experience with the ISBL modules. Interviews are influenced by ethnographic methods and followed six structured questions designed to fit into a twenty-minute interview format [30]. Questions covered what students like best about the ISBL modules, suggestions for improvement, navigation experience, impact on learning, recommendations for future users, and an "Anything else to add" question. Interview notes were taken and analyzed using qualitative data analysis techniques from Grounded Theory to produce a set of themes across student experiences [31].

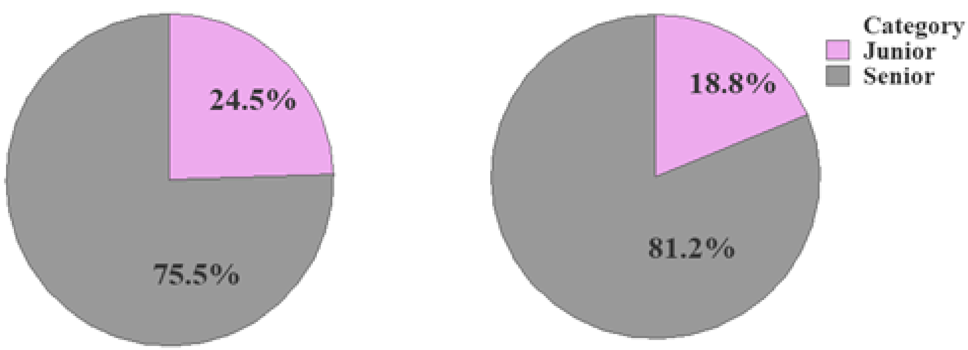
3.5 Student Population

We use the demographics and BFI personality surveys to establish a baseline and ensure that the two groups are comparable. Table 3.1 shows the gender composition of the students in the control and ISBL group. As shown in Figure 3.3(a), most students in both groups are from engineering majors, but the ISBL group has a higher percentage of non-engineering majors (8.2%) compared to 3.1% in the control group (this has important implications for the results related to engineering identity as discussed later). As shown in Figure 3.3(b), most students in both groups are seniors.



ISBL group　　　　Control group

(a) Major



ISBL group　　　　Control group

(b) Semester standing

Figure 3.3. Group composition based on major and semester standing

Table 3. 1. Gender composition of the two groups

	Female	Male	Other
Control group	9.1%	90.9%	0%
ISBL group	17.6%	82.4%	0%

Table 3.2 shows the mean, median, and standard deviation of the five BFI personality dimensions for the two groups. Our two-sample t-tests indicate no statistical differences between the two groups related to these dimensions at a 5% level of significance. As shown in Table 3.3, a two-sample t-test at a 5% significance level indicates no significant statistical difference between the two groups in terms of the average GPA (i.e., we fail to reject $H_0: \mu_{GPA}^{Control} - \mu_{GPA}^{ISBL} = 0$). Figure 3.4 shows that the GPA distribution is also similar for the two groups of students being compared.

Table 3.2. BFI personality test results for the two groups

BFI dimension	Control			ISBL			Test outcome
	Mean	Median	Stdev	Mean	Median	Stdev	p-value
Extroversion	5.636	5	1.782	6.118	6	1.740	0.227
Agreeableness	4.788	4	2.073	4.804	5	1.442	0.969
Conscientiousness	3.82	3	1.67	4.12	4	1.35	0.391
Neuroticism	6.515	6	2.167	6.275	6	1.877	0.603
Openness	4.909	5	1.156	4.980	5	1.407	0.801
Overall	25.668	23	8.848	26.297	26	7.816	2.991

Table 3.3. GPA comparison between the two groups

	Control			ISBL			Test outcome
	Mean	Median	Stdev	Mean	Median	Stdev	p-value
GPA	3.111	3.20	0.531	2.917	2.85	0.623	0.132

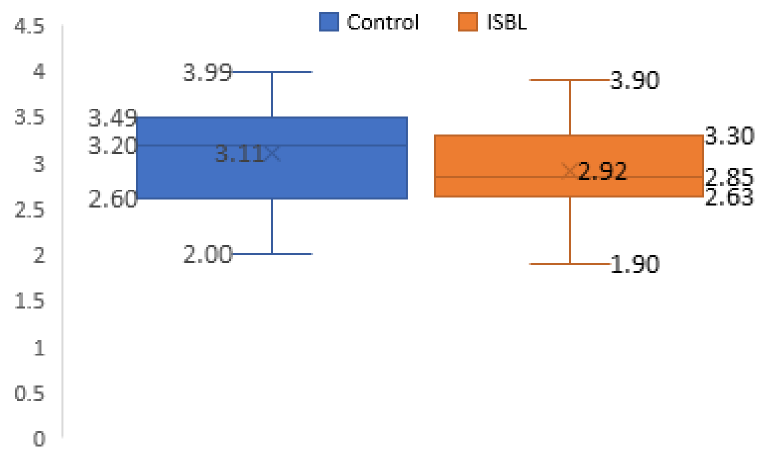


Figure 3. 4. GPA distribution comparison

3.6 Research Hypotheses

Based on the above results, it would be reasonable to assume that the two groups are comparable in terms of academic and personality factors and that any statistical difference observed between the two groups regarding the outcome variables can be attributed to the intervention implemented, i.e., the ISBL modules. More specifically, our experiment aims to investigate the following hypotheses:

1. The ISBL group shows higher motivation than the control group as measured by the IMMS instrument.
2. The ISBL group shows higher levels of experiential learning than the control group as measured by the experiential learning survey.
3. The ISBL group shows higher engineering identity than the control group as measured by the engineering identity instrument.
4. Students in the ISBL group perceive higher levels of learning as measured by the self-assessment questionnaire based on Bloom's taxonomy of learning objectives.

3.7 Quantitative Assessments: Statistical Comparisons and Results

All statistical tests presented in this section are performed at a 5% level of significance. As for the first research hypothesis, Table 3.4 shows the mean, median, and standard deviation of the four dimensions related to motivation as measured by the IMMS instrument for the control and ISBL group. The ISBL group shows a higher mean and median for all IMMS constructs compared to the control group. Especially, our two-sample t-tests indicate a *highly* statistically significant improvement for “Confidence”. For “Relevance”, we barely fail to reject the null hypothesis with a p-value of 0.051, just over the cut-off point of 0.05, deserving of further investigation with additional data. The improvement in motivation can be explained by noting that ISBL is inspired by and resembles real-world situations that the learner may encounter at the future workplace, hence students see higher relevance and report a more positive attitude towards success as they feel more confident about their ability to handle real-world problems.

Table 3. 4. Motivation comparisons (H0: $\mu_{RIMMS}^{Control} - \mu_{RIMMS}^{ISBL} = 0$)

IMMS dimension	Control			ISBL			Test outcome
	Mean	Median	Stdev	Mean	Median	Stdev	p-value
Attention	8.588	8	2.851	9.633	10	3.264	0.126
Relevance	7.059	7	2.51	8.265	8	3.012	0.051
Confidence	6.618	6	2.57	9.286	9	3.075	**0.000****
Satisfaction	9.824	10	3.406	10.83	11	3.406	0.158
Overall	32.9	31	11.337	38.02	38	12.75	0.335

As for the second research hypothesis, Table 3.5 shows the mean, median, and standard deviation of the two constructs investigated via the experiential learning instrument, namely “Environment” and “Utility”. According to the test results, the ISBL group shows a higher level with respect to “Utility” compared to the control group and that the observed difference is *highly* statistically significant. We believe this improvement is because ISBL resembles real-world inspired problems, allowing the students to more clearly see that what they learn is useful and applicable in real-world settings.

Table 3.5. Experiential learning comparisons (H0: $\mu^{Control}_{Experiential} - \mu^{ISBL}_{Experiential} = 0$)

Experiential learning construct	Control			ISBL			Test outcome
	Mean	Median	Stdev	Mean	Median	Stdev	p-value
Environment	17.41	17.5	3.88	17.12	17.0	4.40	0.753
Utility	19.68	18	7.33	24.49	22	9.12	**0.009****
Overall	37.09	35.5	11.21	41.61	39	13.52	0.762

As for the third research hypothesis, Table 3.6 shows the mean, median, and standard deviation of the constructs related to engineering identity. We observe a statistical difference between the two groups for “Recognition”; however, this time the Control group seems to be performing better with respect to this construct. We believe that this finding is primarily due to two reasons: (a) the ISBL group has a higher percentage of non-engineering majors (8.2%) compared to the control group which has only 3.1% non-engineering students as shown in Figure 3.3(a); hence it would be unreasonable to expect a statistically higher engineering identity for the ISBL group; and, (b) the scope and duration of our intervention is too limited/short to make a significant impact on the student’s engineering identity (i.e., we implemented only a few ISBL modules in a single course). There is a need for a longitudinal study over an extended period and multiple courses to investigate the impact of ISBL on engineering identity.

Table 3. 6. Engineering identity comparisons (H_0 : $\mu^{\text{Control}}_{\text{Eng identity}} - \mu^{\text{ISBL}}_{\text{Eng identity}} = 0$)

Engineering identity construct	Control			ISBL			Test outcome
	Mean	Median	Stdev	Mean	Median	Stdev	p-value
Recognition	7.32	6.5	2.86	5.94	6.5	2.33	**0.023***
Interest	5.91	6	2.44	4.92	4	1.88	0.051
Performance	11.15	11	3.71	11.67	10	4.53	0.564
Overall	24.38	23.5	1	22.53	20.5	8.74	0.638

As for the fourth research hypothesis, Table 3.7 shows the mean, median, and standard deviation of the self-assessment results for the control and ISBL groups. Two sample t-tests are performed for every concept/topic related to the ISBL modules used. The results indicate no significant statistical difference between the two groups related to self-assessment, while both groups report the same median for all topics. In conclusion, the results show that the ISBL modules enhanced motivation and experiential learning without any adverse impact on students' self-perceived learning.

Table 3. 7. Self-assessment results (H_0: $\mu^{Control}_{Self-assesment} - \mu^{ISBL}_{Self-assesment} = 0$)

Concept/Topic	Control			ISBL			Test outcome
	Mean	Median	Stdev	Mean	Median	Stdev	p-value
Commercial loans	4.00	4	1.56	3.75	4	1.58	0.523
Effect of inflation	4.09	4	1.40	3.88	4	1.27	0.486
Annual worth analysis	3.82	4	1.66	4.12	4	1.44	0.398
Rate of return analysis	3.82	4	1.45	3.67	4	1.66	0.663
Overall	15.74	16	5.21	15.45	16	4.23	0.792

3.8 Qualitative Assessment

Qualitative interviews about the ISBL module experience were conducted with ten students in the fall of 2020 and the spring of 2021. Themes emerged from the data which support three of the four hypotheses and findings from the results of the quantitative analysis. The first theme for discussion is "Real World Context." For this theme, students discussed the applicability of the ISBL modules for their future careers. To this point, one student stated that the modules were a "nice representation of what you would actually do in the workplace." Similarly, another student said, "looking at real life situations helped understand the data collection." Students also recognized the real-world value of the simulations during the COVID-19 pandemic, as one student mentioned: "It was valuable to have this during a pandemic when we can't actually visit a site." This theme supports both the development of motivation found in the assessments of hypothesis 1 and the recognition of utility found in the assessment of hypothesis 2 as a result of operating in a more real-world context. As one student succinctly put it, you are “seeing the overall picture and not just focused on pizza slices.”

A second theme related to “Engagement” emerged from the interview data. For this theme, students described the ISBL modules as “fun, like playing a game”, “better than a lecture for engagement,” and “made me look forward to using the assignments in class.” Another student summed this up as, “overall, a very interesting part of the course.” This theme supports hypothesis 1 related to motivation. In this interpretation, students become engaged in the modules, and this leads to the development of their confidence as the statistical test results also indicate.

A third theme that emerged related to “Learning about a Career.” In this theme, students described the impact of the ISBL modules on understanding potential career tracks after school. One student stated, “going to be a good experience if I get an internship, would help understand what it would be like to work in this field.” Another student stated that the modules were a “great indicator of what to expect when going into this type of work.” This theme provides some support for hypothesis 3 related to identity development. Although quantitative assessment results did not show a statistical improvement, these qualitative results show that students are learning about a possible career track and additional tracking of career identity over time might eventually lead to significant development in this area.

3.9 Conclusions

In this paper, we proposed and implemented ISBL for teaching and learning engineering economy. ISBL involves an immersive simulation that serves as the context for problem-/project-based learning. Students can make virtual site visits and interact with the simulation in desktop mode (low-immersion) or in VR mode (high-immersion). The statistical comparisons from a controlled experiment conducted in an undergraduate engineering economy course show that ISBL improves motivation and experiential learning. These findings are also manifested in the qualitative user interviews with a sample of research participants.

ISBL modules can be used as in-class examples during lectures, homework/exam problems, or an individual or group project. Implementing ISBL does not require any technology fee or access to special immersive technologies as the simulation software is free for academic use and the simulations can be used on any typical computer. In the implementations discussed in this paper, we replaced a set of traditional homework problems with related ISBL modules without restructuring or modifying other aspects of the course. In order to further facilitate ISBL adoption by other instructors and educational researchers, we publicly share a set of ISBL modules for various STEM topics on the website for our ongoing project available at https://sites.psu.edu/immersivesimulationpbl.

Our experiment results reveal two important areas for future extensions. First, a longitudinal study is needed to assess the effect of ISBL on engineering identity and its related constructs, as intervention in a single course is less likely to make a significant impact on students' engineering identity. Secondly, additional experiments are needed to assess the impact of ISBL on learning. Our self-assessment survey failed to capture a statistical difference between the control and intervention groups, hence we would recommend use of alternative instruments to measure learning.

We hope that this paper and its extensions will encourage the use of immersive simulations in conjunction with PBL in engineering education.

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Chapter 4

Quantification and Impact of Learner Navigation in Immersive Simulation Environments

4.1 Introduction

The results of a comprehensive literature analysis on the use of virtual immersive learning environments in higher education [1] indicates that while there is general interest in studying user interaction with virtual environments, only a small subset of current educational research studies (around 7%) collect and analyze usage and navigation data. Moreover, [1] identify three methods for collecting usage/navigation data: (a) manual, physical observation of the participants; (b) survey instruments and questionnaires; and, (c) usage logs of user activities collected automatically by the virtual platform software.

Manual observation of participants is extremely tedious, is subject to human error, and is only feasible for small studies (in terms of number of participants and length of interaction with the virtual environment). Most well-established and validated survey instruments are primarily designed for assessing overall "usability" and "user experience" and do not provide any data on specific interactions and actions the learner performs within the virtual learning environment. On the other hand, questionnaires that ask for users' freeform response/explanation about their interaction and navigation are opinionated and obtrusive, and often fail to collect data on important details compared to when the user is observed in real time as they interact with the virtual learning environment. Moreover, data logs automatically collected by virtual platforms and software apps are generic (i.e., the same data points are logged regardless of the virtual environment used) hence often do not contain the specific interaction/navigation data needed for educational research studies. As a result, the is a general paucity of scientific evidence on the relationship between learning outcomes and usage/navigation in virtual learning environments. Figure 4.1 summarize an overview of the general experiment.

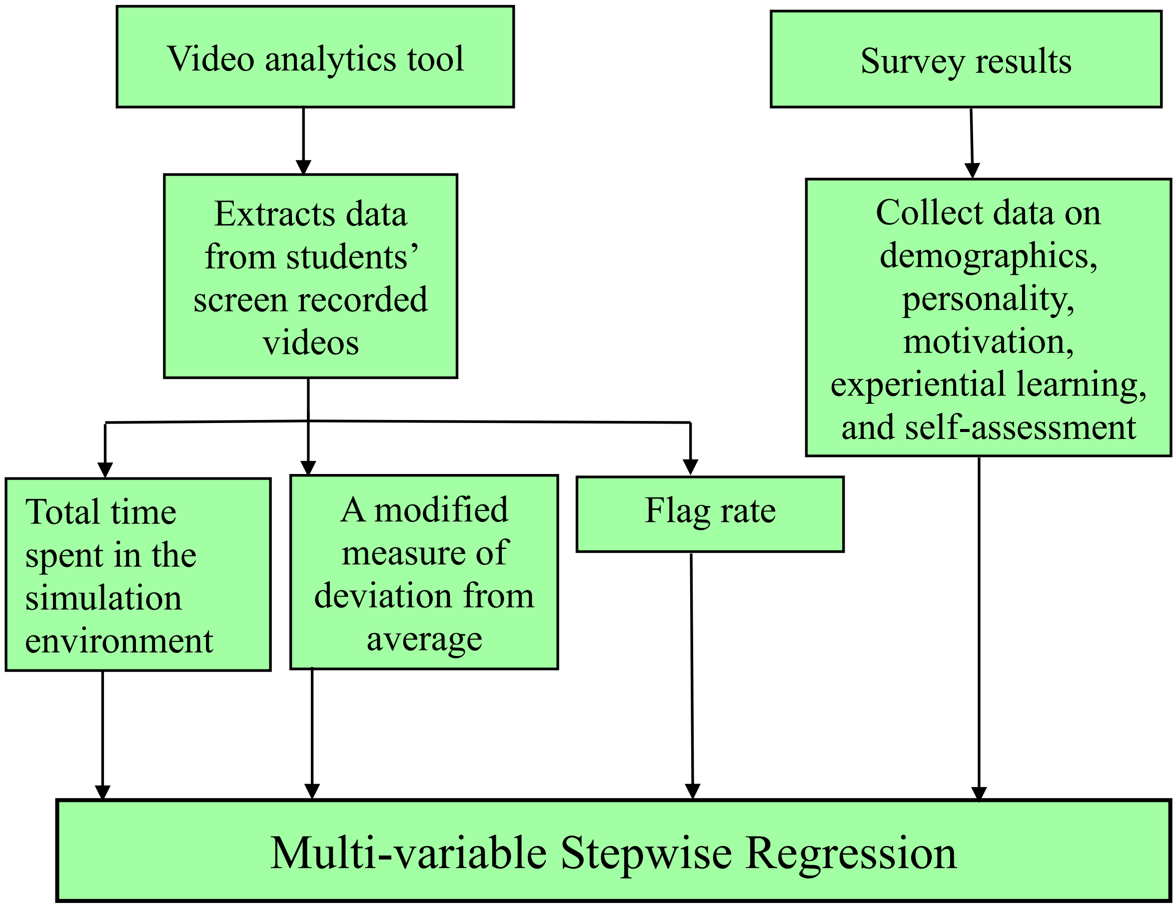

Figure 4. 1. General design of the experiment

4.2 Overview of The Virtual Learning Environment and Course Implementation

We implement sample ISBL modules in an undergraduate course on "object-oriented programming in Java", a required course for the B.S. in Computer Science program at Penn State Abington. The high-level objectives of the course are to enable students to:

- program in an object-oriented language (Java)
- write code to interface databases using Java

- create graphical user interfaces (GUIs) using Java
- understand web-based object-oriented programming and design including the concepts of net-centric computing.
- understand interface prototyping, program design, implementation of both client and server programs, unit testing, and documentation.

The course is structured to be taught online and includes video lectures, online quiz questions for each lecture, homework assignments, a class project, and two exams. The course section used in this study was offered in Spring 2021. The ISBL modules used in the experiments and analysis presented in this paper are related to an airport terminal and aim to mimic a real-life system and object-oriented programming problems. Figure 4.2 provides a screenshot of the immersive simulation used in the ISBL modules. Students are given two weeks to complete each ISBL assignment following the lecture on the respective topic. The document that comes with each module includes a description of the system at hand and the object-oriented programming problems to be solved. Each module is accompanied by a 3D, VR-compatible, animated simulation model that is to be treated as the "real-world system".

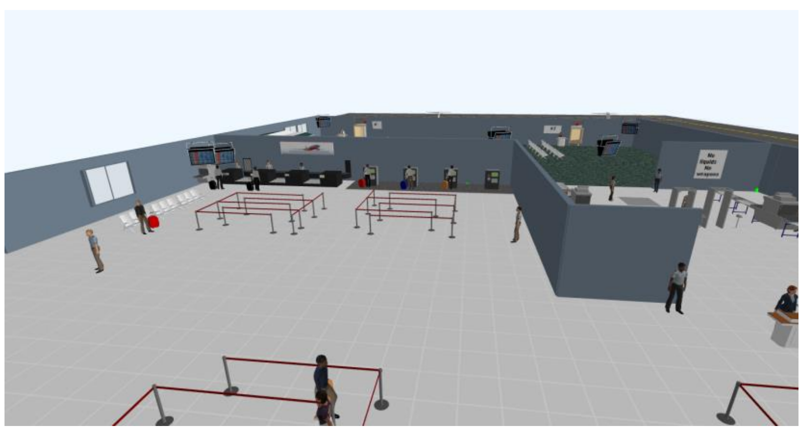

Figure 4. 2. The immersive simulation model of an airport terminal

We developed and implemented three related ISBL modules (i.e., three assignments) defined around the immersive simulation (which serves as the context). In these modules, the student is "hired" as a software engineer to develop an information system using an object-oriented programming language for the airport terminal. Students need to interact with and navigate through the simulation to make observations and collect the necessary data/information needed to complete the assignments. The learning objectives for the three ISBL modules can be summarized as follows:

- Identify relevant classes, attributes of classes, methods of classes, and their relationships to a given problem by observing a real system.
- Develop a pseudocode of the system based on the identified classes and their attributes, methods, and relationships.
- Create a UML class diagram from a pseudocode.
- Import data into the database using SQL scripts.
- Create a CRUD (Create-Read-Update-Delete) database application and a graphical user interface (GUI).
- Test the CRUD application and associated GUI using real/simulated events/test cases.

4.3 Research Data and Methodology

This section describes the research data, our approach to quantification navigation in the simulated environment, and the multi-variable regression analysis experiments.

4.3.1 Data collection

The following instruments/methods are used for data collection (all necessary IRB approvals are obtained prior to our data collection):

- **Demographics Survey:** The demographics survey is used to collect data on the student's gender, race, grade point average (GPA), major, semester standing, prior work experience, and prior experience with computer simulation, and experience with video games.
- **Big-Five Inventory (BFI) Personality Test:** This instrument [1] consists of 10 Likert scale questions and measures five personality traits, namely extroversion, agreeableness, conscientiousness, neuroticism, and openness.

- **Experiential Learning Survey:** Experiential learning or experience-based education is generally referred to settings where learners apply what they learned to solve real-world problems [2]. This survey involves 12 Likert scale questions measuring student's perception of incorporation of active, participatory learning in the course [3]. This instrument consists of four different constructs such as environment, utility, active learning, and relevance. We mainly focus on two of the constructs, namely how effective the *environment* was in students' learning, and how beneficial the hands-on experiment was in terms of *utility* in the student's future activities.
- **Self-assessment based on Bloom's Taxonomy:** In this instrument, adapted from [4] students are asked to rank their perceived level of understanding for various concepts based on six cognitive levels [5]: (1) Remembering relevant knowledge; (2) Understanding, classifying, and explaining the material; (3) Applying the knowledge learned; (4) Analyzing and dividing materials through separating and organizing; (5) Evaluating by examining and criticizing based on standards; (6) Creating solutions to new problems.
- **Screen-recorded videos of interaction with the simulation environment:** We asked students to record their screen while navigating in the simulation environment as they made observations and collected the data needed for solving the ISBL assignments. We then used the proposed video analytics tool to extract data on multiple interaction measures as described in the following section.

4.3.2 Quantifying Learner Navigation in the Simulated Environment via Video Analytics

In order to analyze the collected screen-recorded videos and extract students' navigation data, we use a video analytics tool developed by our research team as part of the overarching NSF project associated with this thesis. Here, we provide a brief overview the main methods used and refer the interested reader to [7] for technical details related to the video analytics tool as the focus of this chapter is on assessing the relationship between learning outcomes and navigation in the simulated environment.

The video analytics tool uses two classification models and provides three statistics (two navigation-related measures and a score related to the recording quality). More specifically, a *multiclassification* convolutional neural network (CNN) is used for predicting time spent at areas of interest in a simulated environment. Once trained based on manually labelled frames, the CNN takes extracted frames from the videos as inputs, runs convolutions over the pixel arrays, and outputs a categorical prediction of the airport area being viewed in each frame. For each student, the tool computes a standard deviation-like measure (hereafter referred to as "Stdev") based on the percentage of time spent in different areas of the simulated environment (e.g., check-in area, security checkpoint, gate, …). For each student, the Stdev measure is computed as follows:

$$Stdev = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \mu_i)^2}{N}}$$

where N denotes the number of areas of interest in the simulated environment, i is the index for the areas ($i = 1,2, \dots, N$), X_i denotes the percentage of time the student under study spent in area i, and μ_i denotes the percentage of time the "average" student spends in area i. In our experiment, μ_i values represent the class average (i.e., percentage of time student participants spend in each area on average).

The intuition and justification behind the proposed Stdev measure can be described as follows. Based on the problems and activities to be completed in each ISBL module, students need to interact with, study and/or collecting data from a certain area or areas of the simulated environment. For example, the first ISBL module used in our experiment asks students to study the "entire" airport to develop a pseudocode of the airport system by identifying relevant object classes and their attributes, methods, and relationships. Therefore, we expect a student that "successfully" completes the ISBL module to spend some time in all areas of the airport. For a class where the majority of students successfully complete the ISBL module (and with some inspiration from the Law of Averages), we expect the class average time for different areas to converge to the "right" time allocation among the areas needed for successful completion of the

ISBL module. For example, if the entire class on average allocates the interaction time uniformly among the check-in, security checkpoint, and gate areas, then we consider a uniform time allocation among these areas to be the appropriate way to navigate the simulated airport for that ISBL module. Consequently, for each student, the greater the discrepancies in their time allocation to different areas, the greater the deviation from a uniform time allocation among the areas, hence the greater the deviation from the proper way to navigate in the simulated environment for that ISBL module.

It is important to clarify that we use *percentage* of time rather than the absolute time to avoid large differences in video lengths to skew the class average and our results. This way, the following two sample students would both have a small Stdev as they both allocated their time almost uniformly among the three areas, even though Student 2 spends twice the total time in the virtual environment.

- Student 1 spends a total of 16 minutes in the simulated airport with 5 minutes (31.25%) spent in check-in area, 6 minutes (37.5%) in security checkpoint, and 5 minutes (31.25%) in the gate area.
- Student 2 spends a total of 32 minutes in the simulated airport with 11 minutes (34.38%) spent in check-in area, 10 minutes (31.25%) in security checkpoint, and 11 minutes (34.38%) in the gate area.

Due to issues that may arise during recording the videos and the unpredictable nature of participants interacting with a computer program, screen recordings may sometimes capture video frames in which the participant navigates away from the simulation program. In the videos that we collected, we sometimes see frames that show the desktop, an empty/black screen, or a different window/application when the student switches between programs in the middle of the assignment (say, the student switches to a chat application to respond to a message and then returns back to the simulation to continue their assignment). These video frames can disrupt the overall accuracy of the multiclassification prediction process as they are not included in the original manually labelled training set. This is a common problem in machine learning and is generally known as *open-set recognition* in which the trained model will still output a prediction on unknown frames (e.g., the CNN will still classify a bank screen as one of the areas in the airport). To combat this issue, a separate *binary classification* model is included in the video analytics tool for identifying frames outside the training set and a "Flag Rate" is reported for each video indicating the percentage of unrecognizable frames in that video. A video with a high Flag Rate contains a high percentage of such frames, hence the less reliable the predictions of the multiclassification CNN. We use this Flag Rate to identify poorly recorded videos and assess the reliability of calculated measures of navigation.

In addition to the Stdev and Flag Rate measures, the video analytics tool also calculates the total time that the student spent in the simulated environment, hereafter referred to as "Total Time", which we also use as a second measure of navigation (besides Stdev) in our multi-variable regression analysis described next.

4.3.3 Multivariable Regression Analysis

A set of multivariable regression analyses are conducted to investigate how/if the two dependent variables (i.e., aggregate measures of experiential learning and self-assessment) can be explained by a set of independent variables or predictors measured via the demographics and BFI surveys and video analytics. Prior to performing the analysis, the normality, homoscedasticity, and linear relationship assumptions are validated. All stepwise regressions are performed at a 5% level of significance. Using a stepwise regression approach, we start with the full model including all explanatory variables followed by sequential elimination of the least statistically significant variables based on a prespecified criterion (i.e., standardized beta coefficient) until the significant predictor(s) are identified to build the final regression model. For instance, equation (1) shows the general model structure, where the students' overall experiential learning score is the dependent variable, a_0 is a constant, x_i $(i = 1, 2, \dots, n)$ denotes the predictor variables, and $a_i(i = 1, 2, \dots, n)$ denotes the standardized coefficient for x_i. A similar general structure will be investigated for the average self-assessment level as shown in equation (2). Tables 4.1 and 4.2 summarize the predictor and dependent variables used in our study, respectively.

$$\text{Overall Experiential Learning} = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n \quad (1)$$

$$\text{Overall Self-Assessment} = b_0 + bx_1 + b_2x_2 + \cdots + b_nx_n \quad (2)$$

Table 4. 1. Predictor variables

Data collection method	Predictor variables	Indicator	Measure
Demographic Survey	Year of birth	Numerical Value	20-26
	Gender	Categorical data	Female, Male, Other
	Race	Categorical data	White, Asian, Hispanic, Black
	Semester Level	Categorical data	Freshman, Sophomore, Junior, Senior
	GPA	Numerical value	0-4.00
	Major	Categorical value	Information science, Other
	Work experience	Categorical value	Yes, No
	Experience with Computer Simulation	Categorical value	Expert, Some experience, None
	Experience with Video games	Categorical value	Expert, Some experience, None
BFI personality traits	Extroversion (Reserved, Sociable)	Score	1-5
	Agreeableness (Generally Trusting, Find faults with others)	Score	1-5
	Conscientiousness (Does a thorough job, tends to be lazy)	Score	1-5
	Neuroticism (Relaxed, Gets nervous easily)	Score	1-5
	Openness (active imagination, artistic interests)	Score	1-5
Interaction in virtual/simulated environment	Total time	Sum of duration of all virtual visits	[0, ∞) in seconds
	Standard deviation (Stdev)	Average deviation from class average for amount of time spent in different areas of the simulation	[0, ∞) in seconds
	Flag rate	Percentage of unrecognized frames in a video	0%-100%

Table 4. 2. Dependent variables

Data collection method	Dependent variables	Indicator	Measure
Experiential learning	Environment	Environment score	1-5
	Utility	Utility Score	1-5
	Overall	Overall average score	1-5
Bloom’s self-assessment	Object oriented programming	Level/Score	1-6
	Database design	Level/Score	1-6
	CRUD development	Level/Score	1-6
	GUI development	Level/Score	1-6
	Overall	Overall	1-6

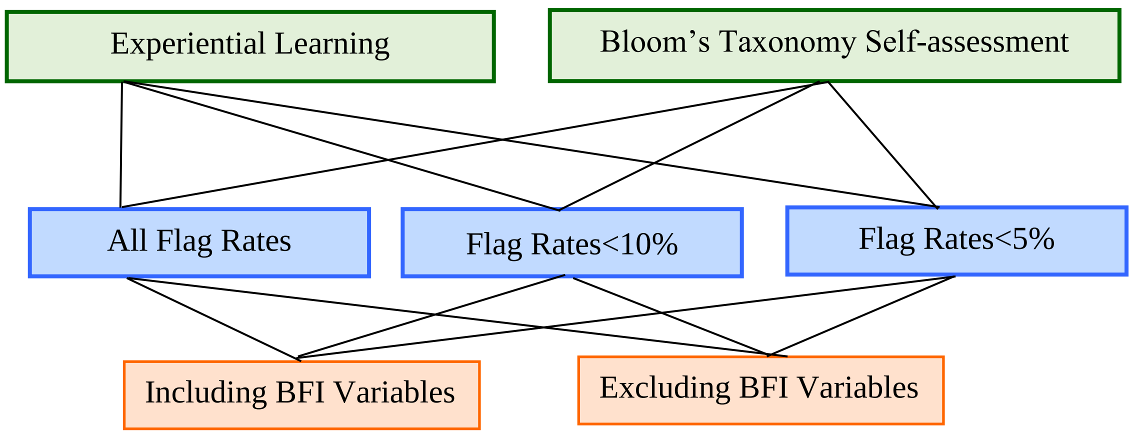

Figure 4. 3. Design of stepwise regression experiment

Figure 4.3 summarizes the stepwise regression experiments. We analyzed a total of twelve models (six for each dependent variable). For instance, we experimented with the following six models for Overall Experiential Learning score as the dependent variable:

- Model 1: All predictor variables in Table 1 and including all student videos regardless of the flag rate.
- Model 2: All predictor variables in Table 1 but only including those videos with a flag rate less than 10%.

- Model 3: All predictor variables in Table 1 but only including those videos with a flag rate less than 5%.
- Model 4: All predictor variables except BFI factors and including all student videos regardless of the flag rate.
- Model 5: All predictor variables except BFI factors and only including those videos with a flag rate less than 10%.
- Model 6: All predictor variables except BFI factors and only including those videos with a flag rate less than 5%.

4.4 Results

This section provides the results of our regression analysis. For the sake of conciseness, and to keep the focus on the role of user-simulation interaction, we only present the results where the interaction-related factors "Total Time" and "Stdev" enter the final regression model.

4.4.1 Predictors of Experiential Learning

Equation (3) presents the resulting regression model when all videos are included (regardless of flag rate) and BFI factors are excluded from the analysis. The model indicates that *year of birth, total time spent in the virtual environment*, and *prior experience with computer simulation* are the most significant predictors of the *Overall Experiential Learning* (OEL) measure. Table 4.3 illustrates the three models returned by the stepwise regression procedure. The adjusted R^2 indicates that 76% of the variance could be explained by the regression model shown in equation (3). There is a negative correlation between the year of birth and OEL, indicating older students tend to report higher levels of experiential learning and OEL score. This could be explained by noting that older students have more life experience and knowledge, which are important factors in developing applied problem-solving skills [6]. Furthermore, current studies in [7] suggest that more mature learners are better at connecting new concepts and their experiences, as well as immediately applying what they already know to new real-world situations. The results also show that the amount of time spent in the virtual/simulated environment is negatively associated with students' OEL score. After further review of student-simulation interaction videos, we partially attribute this negative relationship to the level of familiarity and ability to use/navigate the simulation software. In other words, a portion of the time in the simulation is spent on becoming familiar with and getting used to usage/navigation features. In addition, some of the longer interaction videos indicate that some students spent a significant time navigating to certain parts of the simulated environment that are irrelevant to the learning activity (perhaps they wanted to see what was going on in other parts of the simulation out of curiosity). Therefore, a high Total Time does not necessarily lead to high experiential learning as the regression model also suggests. Lastly, the model suggests a positive correlation between OEL and prior experience with computer simulation. This can be explained in two ways: (a) prior experience with computer simulation enables students to apply/activate their past knowledge/information to build new knowledge and better relate to the ISBL modules; (b) having prior experience with simulation environments allows the student to focus and spend the majority of the interaction time on performing the tasks related to the learning activity, while students without prior experience tend to spend more time on becoming familiar with and getting used to usage/navigation in a new type of environment [8].

$$\begin{aligned}\mathrm{OEL} = \; & -0.827 * \text{Year of birth} - 0.440 * \text{Total time} \\ & + 0.341 * \text{Experience with computer simulation}\end{aligned} \tag{3}$$

Table 4. 3. Predictors of OEL

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.61	0.593	-.786	-5.080	0.00
2	Year of birth	0.71	0.67	-.883	-6.067	0.00
	Total time			-.333	-2.210	0.043
3	Year of birth	0.80	0.76	-.827	-6.597	0.00
	Total time			.440	-3.347	0.005
	Experience with computer simulation			.341	2.619	0.020

Equation (4) shows the regression model including BFI factors when only videos with a flag rate of less than 5% are included in the analysis. The model indicates that *year of birth, doing a thorough job, previous work experience, active imagination,* and the proposed *Stdev* navigation measure are the most significant predictors of the OEL score. The adjusted R^2 suggests that 93% of the variance could be explained by the regression model shown in equation (4). Table 4.4 summarizes the five models returned by the stepwise regression procedure. Once again we see a negative correlation between year of birth and OEL as in the previous model. According to [9], "doing a thorough job" is one of the consciousness personality factors, describing individuals who tend to be more responsible and goal oriented. Students with higher levels of conscientiousness tend to seek their career goals by persistent studying, which can explain higher levels of experiential learning reported by these students. The positive correlation between this personality trait and OEL can also be explained by existing research findings that suggest such personality traits are also expected to enhance students' acceptance of computer-based assessments such as the ISBL modules used in our experiment [10].

The negative correlation between previous work experience and OEL suggests that work experience may reduce experiential learning via ISBL. More experienced students tend to blend the instructions materials with their (often irrelevant) work experience, which could negatively affect their ability in absorbing new concepts [11]. Therefore, having work experience is not necessarily a helpful resource to improve student's experiential learning outcomes. We find a negative correlation between our proposed Stdev navigation measure and OEL, which can be explained as follows. The learning activity for each ISBL module focuses on certain parts/areas of the simulated airport terminal. Since we assume the class average converges to the "appropriate" time allocations among areas in the simulation, then a student that spends too much or insufficient time in the relevant area(s) compared to the class average is most likely not doing the assignment properly, which in turn is expected to negatively affect their OEL score. Lastly, there is a positive correlation between active imagination and OEL, suggesting that active imagination enhances students' overall experiential learning outcomes in ISBL. Active imagination allows students to be more creative and improves their critical thinking skills and ability to find alternative solutions for real-life problems [12]. Since the ISBL modules mimic real-world situations, the observed positive correlation is expected.

$$\text{OEL} = -.264 * \text{Year of birth} + .897 * \text{Thorough job} \\ -.468 * \text{Previous work experience} - .258 * \text{Stdev} \\ +.213 * \text{Active imagination} \qquad (4)$$

Table 4. 4. Predictors of OEL

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.617	0.593	-.786	-5.08	0.00
2	Year of birth	0.80	0.781	-.516	-3.87	0.002
	Thorough job			.512	2.89	0.012
3	Year of birth	0.874	0.847	-.359	-2.86	0.012
	Thorough job			.749	5.30	<0.001
	Prior work experience			-.330	-2.73	0.016
4	Year of birth	0.915	0.889	-.256	-2.23	0.044
	Thorough job			1.030	6.25	<0.001
	Previous work experience			-.474	-4.02	0.001
	Stdev			-.283	-2.50	0.026
5	Year of birth	0.947	0.926*	-.264	-2.81	0.016
	Thorough job			.897	6.24	<.001
	Previous work experience			-.468	-4.85	<0.001
	Stdev			-.258	-2.77	0.017
	Active imagination			.213	2.71	0.019

4.4.2 Predictors of Learner's Self-Assessment

Equation (5) shows the regression model when BFI factors and videos with a flag rate of less than 10% are included in the analysis. The model indicates that *trust, doing a thorough job, year of birth,* and the proposed *Stdev* navigation measure are the most significant predictors of the *overall self-assessment* score. The adjusted R^2 suggests that 92% of the variance could be explained by the regression model in equation (5). Table 4.5 summarizes the four models returned by the stepwise regression procedure. We see a negative correlation between being generally trusting and the overall learners' self-assessment score. Those who introduced themselves as more generally trusting, report a lower self-assessment score. Our literature review did not find specific evidence for the negative relationship between trusting personality and self-assessment scores. As an extension to this study, we believe that further investigation with additional experiment and data could be conducted to understand the impact of trusting personality trait and learner's self-assessment scores. Once again we see a positive correlation between doing a thorough job and the learner's self-assessment as in the previous OEL model. We see a positive correlation between year of birth and the learners' self-assessment, suggesting younger students tend to report higher levels of self-assessment score. This could be explained by the main findings in [14] that indicate younger minds are intrinsically more flexible, exploratory, and adaptable to new pedagogical practices in comparison to their older counterparts, and as our knowledge grows with age, we become less open to new ideas/methods. As a result, younger students seem to better evaluate their own learning abilities. Lastly, we find a similar correlation between Stdev and learner's self-assessment as in the previous model.

$$\begin{aligned} \textit{Overall Self-Assessment} = {} & -1.496 * Trust + 1.591 * Thorough\,Job \\ & +.768 * Year\ of\ birth - .317 * Stdev \end{aligned} \tag{5}$$

Table 4. 5. Predictors of self-assessment

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Trust	0.67	0.63	-.82	-4.52	0.001
2	Trust	0.79	0.75	-1.234	-5.39	<.001
	Thorough job			.546	2.38	.041
3	Trust	0.90	0.86	-1.320	-7.59	<.001
	Thorough job			1.145	4.22	.003
	Year of birth			.623	2.84	.022
4	Trust	0.94	0.92	-1.496	-10.0	<.001
	Thorough job			1.591	5.93	<.001
	Year of birth			.768	4.3	.003
	Stdev			-.317	-2.60	.035

4.5 Conclusions

In this paper, we implemented a set of ISBL modules for teaching and learning in computer science engineering. ISBL provide a learning environment that enables students to interact and navigate through a virtual environment that mimics real-world situations. Students are asked to record their screens while navigating through the virtual/simulated environment as part of their assignments. We then used a video analytics tool to extract navigation data from students' screen recorded videos and performed multivariable regression analysis. We also used a set of surveys to collect data on students' demographics, personality, experiential learning, and self-assessment of learning. We then performed a set of multi-variable regression analyses to characterize and explain the relationship between user-simulation navigation and constructs assessed via survey instruments to determine how/if user navigation in the simulated environment can be a predictor of their learning outcomes. Our results from the multi-variable regression analysis suggest that total time spent in the virtual/simulated environment and modified measure of deviation from average are predictors of OEL and learner's self-assessment.

The result of this study reveals a few gaps to be investigated as future works. First, there is a need for collecting additional data from students' screen recorded videos over an extended period of time to obtain more statistically reliable predictive models. Secondly, we believe that the development and assessment of additional measures of navigation and interaction with simulation environment could be a great addition and a potential future research topic. Lastly, we recommend the development of a system to determine the interaction of other constructs with new navigation metrics assessed via other survey instruments.

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Chapter 5

Conclusions and Future work

In this thesis, we first presented a bibliometric analysis, literature review, and trend analysis over time from the relevant papers published in ASEE proceeding conferences from 1996-2020. The bibliometric analysis and literature review helped us identify the engineering disciplines that used the combination of VR and PBL. Our trend analysis from the 1996-2020 indicated that the use of virtual environments has been increased over time, and this can be attributed to the increased accessibility and affordability of immersive technologies such as VR. Furthermore, we observed that there is a lack of formal assessments for the efficacy of virtual learning environments, which we aimed to address in our analysis of ISBL effectiveness.

We proposed and implemented ISBL for teaching and learning engineering economy. ISBL involves an immersive simulation that serves as the context for problem-/project-based learning. Students can make virtual site visits and interact with the simulation in desktop mode (low-immersion) or in VR mode (high-immersion). The statistical comparisons from a set of controlled experiments performed in an undergraduate engineering economy course show that ISBL improves motivation and experiential learning. These findings are also manifested in the results of qualitative user interviews with a sample of research participants.

We implemented a set of ISBL modules in an undergraduate computer science course. The modules required students to record their videos in order to complete their assignments. We then used a video analytics tool to extract data from students' screen recorded videos and performed multivariable stepwise regression analysis to see if factors related to learner-simulation interaction are predictors of student's learning outcomes, namely experiential learning, and self-perceived level of learning. The results indicate that the total time spent in the simulation and time allocations among different areas within the simulated environment are predictors of experiential learning and students' self-assessment.

There are several limitations in this research which can be improved in future research:

(1) There is a need for longitudinal study over an extended period of time to assess the impact of ISBL on engineering identity and its related constructs.

(2) In our experiment, we did not find any evidence on the statistical significance in terms of learner's self-assessment. We suggest that further investigation with additional experiment is needed to assess the impact of the ISBL on learning, perhaps via analyzing students' actual academic performance (e.g., grades) as opposed to self-assessments.

(3) Time limitations and class sizes limited some of the sample sizes that were available to us in this thesis. Our research team will be collecting additional data from more students for enhanced statistical reliability and deeper analysis on the effectiveness of ISBL on students' learning outcomes in STEM education.

We hope that this research and its extensions will encourage the use of immersive simulations in conjunction with PBL in STEM education. In order to further facilitate ISBL adoption by other instructors and educational researchers, we publicly share a set of ISBL modules for various STEM topics on the website for our ongoing project available at https://sites.psu.edu/immersivesimulationpbl.

Appendices

Appendix A

A detailed result from the experiential learning regression models

Predictors of Experiential Learning

Equation(A.1) presents the resulting regression model when all videos (regardless of flag rate) are included in the analysis. The model indicates that *year of birth*, *doing a thorough job*, *previous work experience and being black* are the most significant predictors of the OEL measure. Table A.1 illustrates the four models returned by the stepwise regression procedure. The adjusted R^2 indicates that 88% of the variance could be explained by the regression model shown in equation (A.1).

$$\mathrm{OEL} = -0.334 * \mathrm{Yearofbirth} + 0.8 * \mathrm{Thorough\ Job} - 0.389 * \mathrm{Previous\ work\ experience} + 0.206 * \mathrm{Black} \quad \text{(A.1)}$$

Table A. 1.Predictors of Experiential Learning

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.617	0.592	-.786	-0.508	0.00
2	Year of birth	0.807	0.781	-.516	-3.87	0.002
	Thorough job			.512	3.383	0.002
3	Year of birth	0.874	0.848	-.359	-2.868	0.012
	Thorough job			.749	.309	0.00
	Previous work experience			-.330	-2.739	0.016
4	Year of birth	0.915	0.88	-.334	3.017	0.008
	Thorough job			.8	6.539	0.00
	Previous work experience			.389	-3.68	0.003
	Black			.206	2.478	0.028

Equation(A.2) presents the resulting regression when all videos with lower than 10% flag rates are included in the analysis. The model indicates that *doing a thorough job, relax, lazy, reserved, and year of birth* are the most significant predictors of the OEL measure. Table A.2 illustrates the five models returned by the stepwise regression procedure. The adjusted R^2 indicates that 99% of the variance could be explained by the regression model shown in equation (A.2).

$$\mathrm{OEL} = 0.842 * \mathrm{Thorough\ job} - 0.307 * \mathrm{Relax} + 0.315 * \mathrm{Lazy} + 0.212 * \mathrm{Reserved} + 0.246 * \mathrm{Year\ of\ birth} \quad (A.2)$$

Table A. 2. predictors of Experiential Learning

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Thorough job	0.801	0.781	0.895	6.347	0.00
2	Thorough job	0.91	0.89	0.784	7.424	0.00
	Relax			-.348	-3.293	0.009
3	Thorough job	0.95	0.94	0.696	8.454	0.00
	Relax			-.304	-3.889	0.005
	Lazy			.245	3.002	0.017
4	Thorough job	0.985	0.976	.67	12.501	0.00
	Relax			-.288	-5.681	0.001
	Lazy			.252	4.787	0.002
	Reserved			.167	3.489	0.01
5	Thorough job	0.99	0.991	.842	14.164	0.001
	Relax			-.307	-9.596	0.001
	Lazy			.315	8.428	0.001
	Reserved			.212	6.539	0.001
	Year of birth			.246	3.482	0.013

Equation(A.3) presents the resulting regression when all videos with lower than 10% flag rates are included and BFI factors are excluded from in the analysis. The model indicates *year of birth* is the only significant predictor of the OEL measure. Table A.3 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 68% of the variance could be explained by the regression model shown in equation (A.3).

$$\mathrm{OEL} = -0.844 * \text{Year of birth} \tag{A.3}$$

Table A. 3. Predictor of OEL

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.713	0.684	-.844	-4.979	0.001

Equation(A.4) presents the resulting regression when all videos with lower than 5% flag rates are included and BFI factors are excluded from in the analysis. The model indicates *year of birth* is the only significant predictor of the OEL measure. Table A.4 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 59% of the variance could be explained by the regression model shown in equation (A.4).

$$\mathrm{OEl} = -0.786 * \text{Year of birth} \tag{A.4}$$

Table A. 4. predictor of OEL

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.617	0.593	-.786	-5.080	0.00

Appendix B

A detailed result from the motivation regression models

Predictors of Motivation

Equation(B.1) presents the resulting regression when all videos(regardless of the flag rates) are included in the analysis. The model indicates that *year of birth* and *relax* are the most significant predictors of the motivation measure. Table B.1 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 70% of the variance could be explained by the regression model shown in equation (B.1).

$$\text{Motivation} = 0.79 * \text{Year of birth} - 0.389 * \text{Relax} \qquad \text{(B.1)}$$

Table B. 1. Predictors of Motivation

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.594	0.569	-.771	-4.841	0.00
2	Year of birth Relax	0.74	0.70	.79 -.389	-5.177 -2.901	0.00 0.011

Equation(B.2) presents the resulting regression when all videos with lower than 10% flag rates are included in the analysis. The model indicates that *year of birth* and *relax* are the most significant predictors of the motivation measure. Table B.2 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 75% of the variance could be explained by the regression model shown in equation (B.2).

$$\text{Motivation} = -0.554 * \text{Year of birth} - 0.515 * \text{Relax} \qquad \text{(B.2)}$$

Table B. 2. Predictors of Motivation

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.574	0.532	-.758	-3.674	0.004
2	Year of birth Relax	0.798	0.753	-.554 -.515	-3.393 -3.152	0.008 0.012

Equation(B.3) presents the resulting regression when all videos with flag rates lower than 5% are included in the analysis. The model indicates that *year of birth* and *relax* are the most significant predictors of the motivation measure. Table B.3 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 75% of the variance could be explained by the regression model shown in equation (B.3).

$$\text{Motivation} = -0.695 * \text{Year of birth} - 0.389 * \text{Relax} \tag{B.3}$$

Table B. 3. Predictors of Motivation

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.594	0.569	-.771	-3.674	0.004
2	Year of birth Relax	0.798	0.753	-.695 -.389	-5.177 2.901	0.00 0.011

Equation(B.4) presents the resulting regression when all videos (regardless of the flag rates) are included, and the BFI factors are excluded in the analysis. The model indicates that *year of birth* is the most significant predictor of the motivation measure. Table B.4 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 56% of the variance could be explained by the regression model shown in equation (B.4).

$$\text{Motivation} = -0.771 * \text{Year of birth} \tag{B.4}$$

Table B. 4. Predictors of Motivation

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.59	0.569	-.771	-4.841	0.00

Equation(B.5) presents the resulting regression when all videos with flag rates lower than 10% are included, and the BFI factors are excluded in the analysis. The model indicates that *year of birth* is the most significant predictor of the motivation measure. Table B.5 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 53% of the variance could be explained by the regression model shown in equation (B.5).

$$\text{Motivation} = -0.758 * \text{Year of birth} \tag{B.5}$$

Table B. 5. Predictors of Motivation

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.574	0.532	-.758	-3.674	0.004

Appendix C

A detailed result from the motivation regression models

Predictors of Learner's Self-Assessment

Equation(C.1) presents the resulting regression when all videos (regardless of the flag rates) are included in the analysis. The model indicates that *trust* and *lazy* are the most significant predictors of the learner's self-assessment measure. Table C.1 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 41% of the variance could be explained by the regression model shown in equation (C.1).

$$\mathrm{Self} - \mathrm{Assessment} \;=\; -0.466 * \mathrm{Trust} - 0.462 * \mathrm{Lazy} \qquad \text{(C.1)}$$

Table C. 1. Predictors of self-assessment

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Trust	0.27	0.22	-.522	-2.449	0.026
2	Trust	0.48	0.41	-.466	-2.494	0.025
	Lazy			-.462	-2.472	0.026

Equation(C.2) presents the resulting regression when all videos (regardless of the flag rates) are included, and the BFI factors are excluded in the analysis. The model indicates that *GPA* is the most significant predictor of the learner's self-assessment measure. Table C.2 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 18% of the variance could be explained by the regression model shown in equation (C.2).

$$\mathrm{Self} - \mathrm{Assessment} \;=\; 0.481 * \mathrm{GPA} \qquad \text{(C.2)}$$

Table C. 2. Predictors of self-assessment

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	GPA	0.231	0.183	.481	2.192	0.044

Equation(C.3) presents the resulting regression when all videos with flag rates lower than 10% are included, and the BFI factors are excluded in the analysis. The model indicates that *GPA* is the most significant predictor of the learner's self-assessment measure. Table C.3 illustrates the model returned by the stepwise regression procedure. The adjusted R^2 indicates that 28% of the variance could be explained by the regression model shown in equation (C.3).

$$\text{Self} - \text{Assessment} = 0.588 * \text{GPA} \tag{C.3}$$

Table C. 3. Predictors of self-assessment

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	GPA	0.346	0.281	.588	2.30	0.044