International Journal of Engineering Education Vol. 40, No. 4, pp. 873–887, 2024
Printed in Great Britain
0949-149X/91 $3.00+0.00

Investigating the Impact of Learners' Time Allocation in Immersive Simulation-Based Learning Environments*

MAHGOL NOWPARVAR[1], NOAH SORIANO[2], SABAHATTIN G. OZDEN[3], PARHUM DELGOSHAEI[1], OMAR ASHOUR[4] and ASHKAN NEGAHBAN[1]
[1]School of Graduate Professional Studies, The Pennsylvania State University, Malvern, Pennsylvania, USA.
E-mail: mahgolnowparvar@gmail.com; pud18@psu.edu; aun85@psu.edu
[2]College of Information Sciences and Technology, The Pennsylvania State University, University Park, Pennsylvania, USA.
E-mail: nfs5267@psu.edu
[3]Division of Science and Engineering, Penn State Abington, Abington, Pennsylvania, USA. E-mail: sgo7@psu.edu
[4]Department of Industrial Engineering, Penn State Behrend, Erie, Pennsylvania, USA. E-mail: oma110@psu.edu

With the increasing use of virtual simulated environments and immersive technologies in STEM education and workforce training, it is becoming increasingly important to study and understand how learners' interactions and navigation in virtual environments affect their learning and skill development. In this paper, we quantify and assess the effect of learners' navigation in an immersive simulated environment on learning outcomes, where navigation is characterized by the total time spent in the simulation and time allocations to different areas within the virtual environment. We implement a set of immersive simulation-based learning (ISBL) modules in an undergraduate computer science course with eighteen students and record their screen as they navigate in the simulation environment to perform the tasks needed to complete the ISBL assignments. We use a video analytics tool to process and analyze the videos and collect statistics related to a set of navigation-related measures for each student. We also use surveys to collect data on students' demographics, prior knowledge and experience, personality, experiential learning, and self-assessment of learning. We then perform a set of multivariable regression analyses to characterize and explain the relationship between navigation measures and constructs assessed via survey instruments to determine how/if users' navigation in the simulated environment can be a predictor of their learning outcomes. The results indicate that the total time spent in the simulation and the distribution of time allocations among different areas within the simulated environment are predictors of experiential learning and students' self-assessment of learning.

Keywords: simulation-based learning; immersive technologies; human-computer interaction; video analytics

1. Introduction

The results of a comprehensive literature analysis on 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, the reviewed papers reveal that there are primarily three methods that are used 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 by the virtual platform software. Each of these methods has its own shortcomings for educational research. 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). On the other hand, available survey instruments are primarily designed for assessing the overall "usability" and "user experience" and do not provide any data on specific interactions and actions that the learner performs within the virtual learning environment, hence fail to capture many aspects of learner-simulation interaction that are critical to educational research. 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 that are automatically collected by software platforms and apps only provide *generic* usage/navigation information (i.e., the same data points are logged for all virtual environments), hence such data logs often do not contain the type of user-simulation interaction/navigation data needed for investigating specific research questions in educational research studies.

As a result, there is a general paucity of scientific evidence on the relationship between learning outcomes and usage/navigation in virtual simulated environments. The work presented in this paper is part of an overarching STEM educational research project (summarized in Fig. 1) and takes a first step toward addressing the above gap. More specifically, the contributions of this paper are:

* Accepted 9 May 2024.

(a) This paper is among a small percentage of studies that takes a *quantitative* approach toward measuring and studying learner-simulation interactions. As mentioned earlier, a comprehensive literature review shows that only 7% of studies collect interaction information and primarily do so in a *qualitative* manner via questionnaires and survey instruments [1].
(b) This paper performs a set of multivariable regression analyses to investigate how/if navigation-related factors are predictors of certain learning outcomes. Our statistical results indicate that the total time spent in the simulation and the distribution of time allocations among different areas within the simulated environment are predictors of experiential learning and students' self-assessment of learning.
(c) From a learning analytics perspective, this study shows the application of a machine learning-based video analytics tool to extract navigation-related statistics from screen recorded videos of students' interactions with a virtual simulated environment.

The remainder of the paper is organized as follows. Section 2 provides a review of common ways of assessing user interaction in simulated learning environments. Section 3 describes the immersive simulation-based learning modules implemented in an undergraduate computer science course as part of our research experiments. Section 4 summarizes the data collection, video analytics for extracting user-simulation interaction from screen recorded videos, and statistical models. Section 5 presents the regression results and main findings. Section 6 provides a discussion on the relevance to and implications for engineering education. Finally, conclusions and future research opportunities are discussed in Section 7.

2. Literature Review

This section provides an overview of common approaches used in educational research papers for assessing user interaction with simulated learning environments. A comprehensive review of virtual reality (VR) applications in higher education [1] shows that despite a general research interest in user interaction with virtual environments, only a small number of papers (7%) collect and analyze usage and navigation data. A handful utilized manual, physical observation of the participants, which is a tedious task and prone to human errors by the observer. Other papers that study usage and navigation primarily used surveys, which are subjective and prone to bias [2], and only provide *qualitative* data. In addition, participant responses to open-ended questions can be incomplete as the full interactive experience is not tracked, recorded, or evaluated. Despite their pitfalls, traditional data

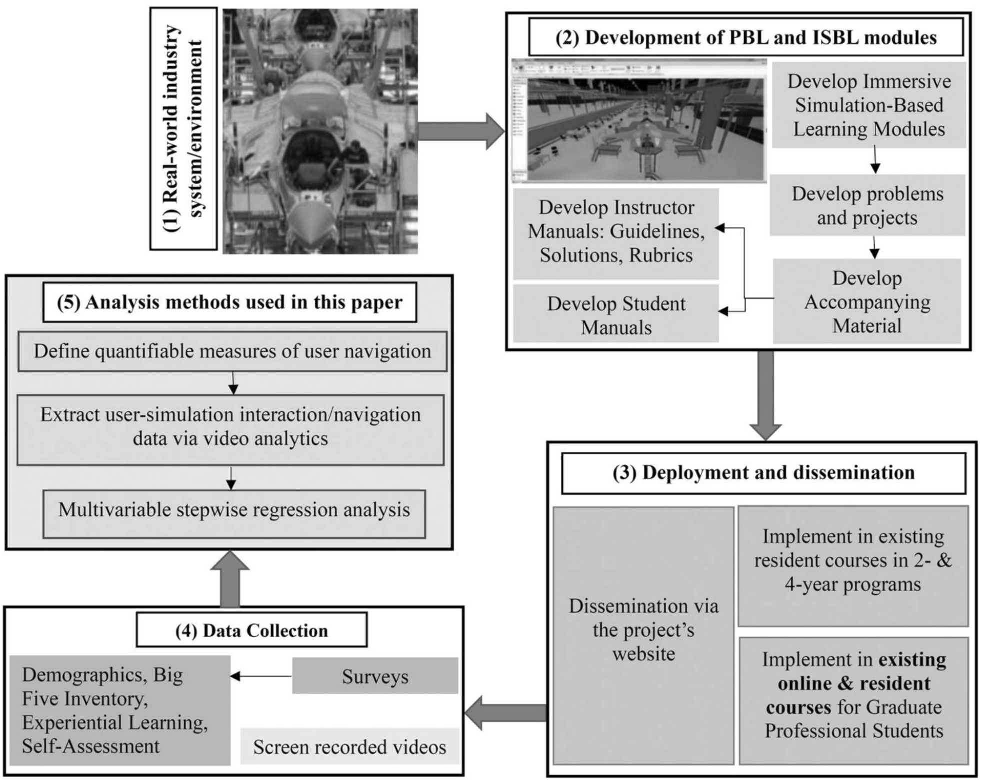

Fig. 1. Summary of the overarching NSF project and analysis methods used in this paper.

collection methods such as surveys/questionnaires and manual observation remain the primary methods in educational research studies for collecting information on learner interactions in simulated environments. We summarize a sample of these studies in this section.

In [3], undergraduate students are asked to write a paper on how a VR learning environment compares to viewing a standard classroom slideshow. In an experiment related to analyzing player presence in computer games [4], the research team concluded that physical observation of participant interaction is too tedious, hence they resorted to collecting qualitative responses from their participants. Researchers in [5] investigate user interactions in mixed-reality teaching and learning environments by manually reviewing and labelling the videos collected using a screen capture tool. In another study [6], the authors assess two levels of immersive VR simulation to teach the skill of decontamination to nursing students. Following initial training, participants who completed either of the two interventions took part in a focus group interview, which was audiotaped and transcribed to analyze students' satisfaction and experience with the two different VR simulation formats.

In [7], 147 undergraduate students watched a 360-degree video of a YouTuber traveling through a city by car. The students were divided into two groups, a group that viewed the video through a VR headset, and the other group who watched the video on a 2D screen monitor. The research team screen recorded the participants' viewing behavior, devised space quadrants in the 360 video, and measured changes in an omnidirectional movement space. Then, the researchers manually reviewed the 147 videos and tracked each user's time spent looking at each video quadrant space through tedious manual measurements. In another study [8], a 3D virtual simulation of a retail store was used with the objective to quantify interest in the rack and aisle design by measuring "exposure intensity" (i.e., how long they are seen). The research team manually tracked the time each participant spent observing and interacting with different product racks, which required a significant amount of time and effort that could be saved if an automated video analytics tool like the one utilized in this paper was used to track the time each participant spends looking at a given location. For a list of other papers that use surveys/questionnaires, manual observations, and/or data logs to study learner interactions and navigation in simulated environments, see [9–13].

The inefficiency and inadequacy of manual and traditional data collection approaches explain why the literature contains limited analysis of user interaction/navigation in virtual simulated learning environments despite the general consensus on its importance. This paper contributes to filling this research gap in the current literature by taking a quantitative approach toward measuring learner navigation in an immersive simulated environment and providing statistical evidence on navigation-related factors as predictors of experiential learning and students' self-assessment of learning.

3. Overview of The Virtual Learning Environment and Course Implementation

This section describes the immersive simulation-based learning modules and their implementation in an undergraduate programming course as part of our research experiments to measure learner navigation in immersive simulations and study its relationship with learning outcomes.

3.1 Immersive Simulation-Based Learning (ISBL)

The virtual learning environments used in our experiments fall under Immersive Simulation-Based Learning (ISBL). ISBL involves the use of an immersive simulated environment which serves as the context for problem-based learning (PBL). The integration of immersive technologies with PBL enables utilizing the advantages of both paradigms to improve critical thinking and problem-solving skills and enhance students' motivation and overall learning experience [14, 15]. More specifically, an ISBL module consists of:

(a) An immersive simulated environment that models a real system and serves as the context for technology-enhanced PBL.
(b) A set of *entities* in the simulated environment that are processed, assembled, produced, stored, or transported. Depending on the context being simulated, these entities can represent people, products, raw material, or information flowing in the simulated system.
(c) A set of *processes* in the simulation that model the stages or stations that the entities go through during the simulation run.
(d) A *PBL activity* defined around the context and inspired by problems related to the real-world system modeled in the simulated environment.

The integration of an immersive simulated environment with PBL also enables ISBL to support and augment the pedagogical and psychological theories associated with traditional PBL, namely:

- *Constructivism Theory* [16]: This theory suggests that learners construct their mental models and interpretations of the real world through cognitive and interpretive activities that accommodate new ideas/phenomena with prior knowledge. In ISBL, the immersive simulation serves as the context and provides an environment to interact with, which enables knowledge to be constructed via interactions with the virtual environment and indexed by relevant contexts.

- *Information Processing Approach to Learning* theory [17]: The three principles of this theory are present in ISBL to support long-lasting development of critical thinking and problem-solving skills by: (a) activating prior knowledge related to the context under study; (b) enabling a contextually enriched learning environment through an immersive simulation that mimics a real-world situation; and, (c) allowing learners to expand their prior knowledge to solve a realistic and practical problem.
- *Self-determination Theory* [18]: This theory promotes *autonomous* motivators in contrast to traditional learning and teaching methods that are primarily based on *controlled* motivators such as rewards and punishments (e.g., passing or failing a test). Such controlled motivators can lead to superficial learning and cause a sense of stress and anxiety. ISBL aligns with this theory as it enables students to incorporate their views and take greater responsibility for their learning, thus promoting autonomous motivators.
- *Adult Learning Theory* [19]: ISBL enables the main pillars of this theory 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.

It is important to note that the assessment of ISBL as an intervention is out of the scope of this paper. We refer the interested reader to [20–23] for a sample of studies on the effectiveness of ISBL for teaching and learning. Instead, the focus of this paper is on learner-simulation interaction, and in particular, on the quantification of learner navigation in an immersive simulated environment to investigate whether navigation-related factors can serve as statistical predictors of certain learning outcomes. To that end, we chose ISBL as a testbed for our research experiments.

3.2 Course Description and Sample ISBL Modules Implemented

We implement a set of ISBL modules in an undergraduate course on "object-oriented programming in Java", a required course for the B.S. in Computer Science program at The Pennsylvania State University, Abington Campus. 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.
- Implement web-based object-oriented programming and design using net-centric computing concepts.
- Perform 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 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 object-oriented programming problems that arise in a real-life airport system. Each module is accompanied by a three-dimensional, VR-compatible, animated simulation model that is to be treated as the "real-world system". Fig. 2 provides a screenshot of the immersive simulation used in the ISBL modules. Students are given two weeks to complete

Fig. 2. The immersive simulation model of an airport terminal.

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.

We developed and implemented three related ISBL modules (i.e., three assignments) defined around the immersive airport simulation (which serves as the context for the assignments). In these modules, the student is "hired" as a software engineer to develop an information system for the airport terminal using an object-oriented programming language. 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.
- Collect and import operational 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 under various events/test cases.

4. Research Data and Analysis Methodology

Fig. 3 summarizes the research data and analysis methodology. Our research experiments include a total of 18 students. We screen record the students' virtual tours as they navigate in the simulation environment to perform the tasks needed to complete their ISBL assignments. We then use a video analytics tool to process and analyze the videos and collect statistics on navigation-related measures for each student. In addition, we use a set of surveys to collect data on students' demographics, academic background and prior preparation, personality type, experiential learning, and self-assessment of learning. The navigation data and survey data are then used to perform a set of multivariable regression analyses to determine how/if users' navigation in the simulated environment can be a statistical predictor of their learning outcomes. The remainder of this section describes these steps in more detail.

We use the above methodology to explore the following research questions: (1) Is the total time spent in the simulation environment a statistical predictor of experiential learning and self-assessment of learning? (2) Is the distribution of time allocations to different areas within the virtual environment a statistical predictor of experiential learning and self-assessment of learning? And, (3) can a combination of the above navigation-related factors and learners' demographics, personality type, prior work experience, and past experience with computer simulations be used to predict experiential learning and self-assessment of learning in the context of ISBL?

4.1 Data Collection

The following instruments/methods are used for data collection (IRB approval was obtained prior to data collection):

- *Demographics and academic background survey:* We collect data on each student's gender, race, grade point average (GPA), major, semester standing, prior work experience, prior experience with computer simulation, and experience with video games.
- *Big-Five Inventory (BFI) Personality Test:* This instrument [24] consists of 10 Likert scale questions and measures five personality traits, namely extraversion, agreeableness, conscientiousness, neuroticism, and openness.
- *Experiential Learning Survey:* Experiential learning or experience-based learning is generally

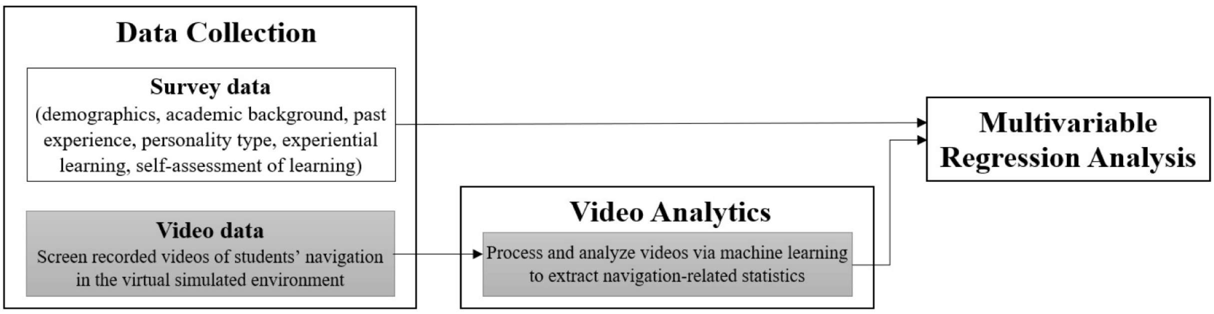

Fig. 3. Research data and analysis methodology.

referred to actively applying knowledge and skills to solve real-world problems [25]. This survey involves 12 Likert scale questions measuring students' perception of incorporation of active, participatory learning in the course [26]. This instrument consists of four different constructs, namely 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 students' future activities.

- *Self-assessment based on Bloom's Taxonomy:* In this instrument, adapted from [27], students rank their perceived level of understanding for various concepts based on six cognitive levels from the Bloom's Taxonomy [28]: (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 screen record students' navigation in the virtual environment as they interact with the simulation, make observations, and collect the data needed for solving the ISBL assignments. We then use a video analytics tool based on machine learning techniques to extract data on navigation measures as described in the following subsection.

4.2 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 summarized in Fig. 1. Here, we provide a brief overview of the main methods used and refer the interested reader to [29] for technical details related to the video analytics tool as the focus of this paper is on assessing the relationship between learning outcomes and navigation in the simulated environment, and as space limitations preclude presenting a complete description of the video analytics tool in this paper.

The video analytics tool uses two classification models and provides three statistics: two navigation-related measures and a score related to video quality in terms of noisy data. 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. The tool tracks the time spent in each area of the airport simulation model (e.g., check-in area, security checkpoint, departure gate, . . .), and 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. For each student, the *Stdev* measure is given by:

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

where N denotes the number of areas of interest in the simulated environment, i is the index for the areas $(i = 1, 2, \ldots, N)$, 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 study, μ_i values represent the class average for area i, that is, percentage of time student participants spend in each area i on average. In essence, this navigation measure calculates the deviation from the average distribution of time allocations among different areas within the simulated environment, in our case, the airport terminal.

The intuition and justification behind the proposed *Stdev* navigation 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 collect 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 every area of the airport. For a class where the majority of students successfully complete the ISBL module (along with additional inspiration from the Law of Large Numbers), we expect the class's average time distributions for different areas to converge to the "appropriate" time allocation among the areas as 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 departure 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 compared to the average time allocations, the greater the deviation from the proper way of navigating the simulated environment for that ISBL module, which is captured by a larger *Stdev* value.

It is important to clarify that we use *percentage* of time rather than the absolute amount of time to avoid differences in video lengths to skew the class average and our results. This way, the following two sample students would both report a small *Stdev* value 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 activity (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 predictions as such frames 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 multiclassification CNN will still classify a blank 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, decreasing the reliability of the predictions by the multiclassification CNN and the estimated time allocations. We use this Flag Rate to identify poorly recorded videos and to 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 a student spends in the simulated environment, hereafter referred to as "Total Time", which we will use as a second measure of navigation (besides *Stdev*) in our multivariable regression analysis described in the following subsection.

4.3 Multivariable Regression Analysis

A set of multivariable regression analyses are conducted to investigate how/if 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. We use a forward stepwise regression approach which forms a prediction model from the bottom up from a set of independent variables by entering the variables into the prediction model one at a time in a series of steps. More specifically, at each step, the variable that, in addition to the previously entered variables, would result in the maximum increase in the explained percentage of variance of the dependent variable will be added to the prediction model. Equation (1) shows the general model structure with all n predictor variables, where the students' overall experiential learning score is the dependent variable, a_0 is a constant, x_j $(j = 1, 2, \ldots, n)$ denotes the predictor variables, and a_j $(j = 1, 2, \ldots, n)$ denotes the standardized coefficient for x_j. A similar general structure will be investigated for the overall self-assessment level as shown in Equation (2). Tables 1 and 2 summarize the predictor and dependent variables, respectively.

$$\textit{Overall Experiential Learning} = a_0 + a_1x_1 + a_2x_2 + \cdots + a_nx_n \tag{1}$$

$$\textit{Overall Self-Assessment} = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \tag{2}$$

Fig. 4 summarizes the stepwise regression experiments. For instance, we experimented with the following six models for *Overall Experiential Learning* score as the dependent variable (similarly, a set of six models were analyzed for the overall self-assessment score):

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

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

Table 1. Predictor variables considered in the multivariable regression analysis

Data collection method	Predictor variables	Data type/indicator	Measure
Demographics survey	Year of birth (age)	Numerical	20–26
	Gender	Categorical	Female, Male, Other
	Race	Categorical	White, Asian, Hispanic, Black, Other
	Semester standing	Categorical	Freshman, Sophomore, Junior, Senior
	GPA	Numerical	0–4.00
	Major	Categorical	Information science, Other
	Work experience	Categorical	Yes, No
	Experience with computer simulation	Categorical	Expert, Some experience, None
	Experience with video games	Categorical	Expert, Some experience, None
BFI personality traits	Extraversion (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 (has active imagination, has artistic interests)	Score	1–5
Time allocations in the simulated environment	Total time	Sum of duration of all virtual visits	$[0, \infty)$ in seconds
	Standard deviation (*Stdev*)	Deviation from the average time allocations to different areas of the simulation	$[0, \infty)$ in seconds
	Flag rate	Percentage of unrecognized frames in a video	0%–100%

Table 2. Dependent variables considered in the multivariable regression analysis

Data collection method	Dependent variables	Indicator	Measure
Experiential Learning Survey	Environment	Environment score	1–5
	Utility	Utility Score	1–5
	Overall	Overall average score	1–5
Bloom's Self-Assessment Survey	Topic 1: Object oriented programming	Score for Topic 1	1–6
	Topic 2: Database design	Score for Topic 2	1–6
	Topic 3: CRUD development	Score for Topic 3	1–6
	Topic 4: GUI development	Score for Topic 4	1–6
	Overall self-assessment	Overall score	1–6

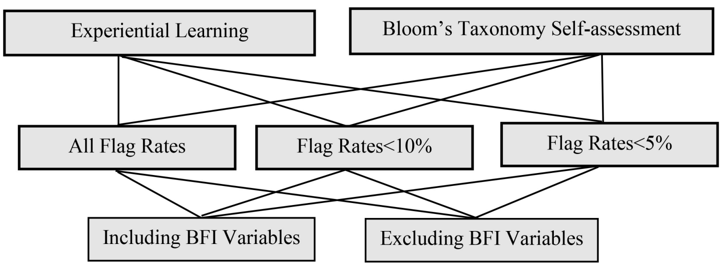

Fig. 4. Design of stepwise regression experiments.

5. Results

This section presents the results of our regression analysis and supporting evidence from the literature to further justify the resulting prediction models. For the sake of conciseness, and to keep the focus on the role of learner navigation in the simulated environment, we only present the results where the navigation factors "Total Time" and "*Stdev*" enter the final regression model.

5.1 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 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).

$$OEL = -0.827 * Year\ of\ birth - 0.440 * Total\ time + 0.341 * Experience\ with\ computer\ simulation \quad (3)$$

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 relationship can be explained by noting that older students have more life experience and knowledge, which previous studies have shown to be important factors in developing applied problem-solving skills [30]. Furthermore, as suggested in [31], more mature learners can easily connect the new concepts to their experience, and immediately apply what they already know to new real-world situations, hence a negative correlation between year of birth of OEL is expected.

Equation (3) also indicates that the total 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 regression model in Equation (3) 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 who lack such prior experience tend to spend more time on becoming familiar with and getting used to usage/navigation in a new type of environment as also observed in [32].

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 summarizes the five models returned by the stepwise regression procedure.

$$OEL = -0.264 * Year\ of\ birth + 0.897 * Thorough\ job - 0.468 * Previous\ work\ experience - 0.258 * Stdev + 0.213 * Active\ imagination \quad (4)$$

Once again, we see a negative correlation between year of birth and OEL as in the previous model. "Doing a thorough job" also enters the

Table 3. Predictors of the Overall Experiential Learning (OEL) score excluding BFI factors

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.61	0.593	–0.786	–5.080	0.00
2	Year of birth	0.71	0.67	–0.883	–6.067	0.00
	Total time			–0.333	–2.210	0.043
3	Year of birth	0.80	0.76	–0.827	–6.597	0.00
	Total time			–0.440	–3.347	0.005
	Experience with computer simulation			0.341	2.619	0.020

Table 4. Predictors of the Overall Experiential Learning (OEL) score including BFI factors

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Year of birth	0.617	0.593	–0.786	–5.080	0.00
2	Year of birth	0.80	0.781	–0.516	–3.870	0.002
	Thorough job			0.512	2.894	0.012
3	Year of birth	0.874	0.847	–0.359	–2.868	0.012
	Thorough job			0.749	5.309	<0.001
	Prior work experience			–0.330	–2.739	0.016
4	Year of birth	0.915	0.889	–0.256	–2.231	0.044
	Thorough job			1.030	6.256	<0.001
	Previous work experience			–0.474	–4.025	0.001
	Stdev			–0.283	–2.502	0.026
5	Year of birth	0.947	0.926	–0.264	–2.812	0.016
	Thorough job			0.897	6.245	<0.001
	Previous work experience			–0.468	–4.854	<0.001
	Stdev			–0.258	–2.772	0.017
	Active imagination			0.213	2.717	0.019

regression model, which is one of the conscientiousness 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 OEL reported by these students. The positive correlation between this personality factor 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 [33]. Furthermore, this finding (and the order of entry of this trait in the prediction model) is supported by the findings of a recent meta-analysis in [34] that identifies this personality trait as the one with the most substantial association with academic achievement.

The negative correlation between previous work experience and OEL can be explained by previous research findings that suggest 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 [35]. Therefore, having work experience is not necessarily a helpful resource to improve student's experiential learning outcomes, especially if the past work experience is not related to the context at hand, explaining the negative correlation reported in the regression model.

We find a negative correlation between the *Stdev* navigation measure and OEL, which can be explained as follows. As described previously, the learning activity for each ISBL module focuses on certain 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. Therefore, we expect a large deviation from the average distribution of time allocations among areas in the simulated environment to negatively affect the OEL score as also indicated by Equation (4).

Lastly, Equation (4) indicates a positive correlation between active imagination and OEL, suggesting that active imagination enhances students' overall experiential learning outcome. From previous studies, we know active imagination allows students to be more creative and improves their critical thinking skills and ability to find alternative solutions for real-life problems [36]. Since the ISBL modules mimic real-world situations, the observed positive correlation is expected.

5.2 Predictors of Self-Assessment of Learning

Equation (5) shows the regression model when BFI factors and videos with a flag rate of less than 10% are considered. The model indicates that *being generally trusting, doing a thorough job, year of birth*, and the *Stdev* navigation measure are the most significant predictors of the *overall self-assessment* score. The adjusted R^2 suggests that 92% of the variance can explained by the regression model in Equation (5). Table 5 shows the models returned by the stepwise regression procedure. Once again, we see a positive correlation between doing a thorough job and learners' self-assessment as justified previously for the case of OEL. 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 attributed to differences

Table 5. Predictors of learner's self-assessment

Model	Predictor variables	R^2	Adjusted R^2	Standardized Beta	t-value	Sig.
1	Trusting	0.67	0.63	–0.82	–4.527	0.001
2	Trusting	0.79	0.75	–1.234	–5.392	<0.001
	Thorough job			0.546	2.388	0.041
3	Trusting	0.90	0.86	–1.320	–7.595	<0.001
	Thorough job			1.145	4.220	0.003
	Year of birth			0.623	2.844	0.022
4	Trusting	0.94	0.92	–1.496	–10.07	<0.001
	Thorough job			1.591	5.935	<0.001
	Year of birth			0.768	4.369	0.003
	Stdev			–0.317	–2.609	0.035

between younger and more mature students in social desirability bias [37] which includes over-reporting desirable attributes, in this case self-assessment of learning. We find a similar correlation between *Stdev* and learner's self-assessment as in the previous model indicating that a larger deviation from the average time allocation distribution has a negative impact on the overall self-assessment of learning as justified previously.

$$\begin{aligned}&\textit{Overall Self-Assessment}\\&\quad = 1.591*\textit{Thorough Job} + 0.768*\textit{Year of birth}\\&\quad -0.317*\textit{Stdev} - 1.496*\textit{Trusting}\end{aligned} \tag{5}$$

Lastly, we see a negative correlation between being generally trusting and the overall learners' self-assessment score. Students who identified themselves as more generally trusting report a lower self-assessment score. Both positive [38] and negative [39] correlations between this personality trait and student achievement have been previously reported in the literature. Therefore, this finding highlights a gap and an important area for future educational research to enhance our understanding of the impact of such personality traits on learner's perception of their own learning.

In summary, we wanted to investigate the impact of learner navigation in immersive simulated environments by determining if and how users' time allocation in the virtual environment can be a predictor of their learning outcomes. The above statistical results indicate that navigation-related measures such as the total time spent in the simulation and the distribution of time allocations among different areas within the simulated environment are predictors of experiential learning and students' self-assessment of learning. These results contribute to the existing body of knowledge by addressing the general lack of quantitative analysis of user-simulation interaction in current educational research studies, and by highlighting the potential value of further research on the role of interaction and navigation in immersive simulation-based learning.

6. Discussions: Relevance to Engineering Education

In engineering education, the value of experiential learning and inquiry-based learning through real-world experiences and experimentation is well-established as reflected by the fact that internships, industry projects, and laboratory courses are recognized as key components of many undergraduate and graduate engineering programs. In recent years, technological advancements have enabled *virtual* inquiry-based and experiential learning via digital simulations and immersive technologies. Some of the most common examples include virtual field trips [40], where students perform site visits in 360-degree panoramic VR rather than physically visiting a real-world site, and virtual laboratories [41], where students interact with virtual equipment and materials, and conduct lab experiments in a technology-mediated manner using a simulation or emulation of a physical lab. One of the main drivers behind the growing application of immersive simulations in engineering education is that they can replace real-world experimentation and augment inquiry-based learning by enabling low-cost and risk-free learning experiences, where learners' interactions within a simulated environment enable knowledge and skill development. Other drivers behind the ongoing shift to immersive simulations are the emergence of online degrees and switching to remote learning during the COVID-19 pandemic.

The growing use of virtual simulated environments in engineering education necessitates a better understanding of how learning occurs in such environments by measuring the relationships between learning outcomes and learners' usage and navigation in virtual settings as well as their demographics, personality traits (say, technology acceptance), and prior experiences [42]. A recent article [15] on the ongoing transition in engineering education from physical experimentation to immersive simulated learning environments highlights *learner-simulation interaction* as an important area for future educational research to address the existing knowledge gap related to teaching and learning via immersive simulations. Quantification and understanding of the role of learner-simulation interaction can help guide and optimize the design of immersive simulated environments to enhance learner engagement, and consequently, students' learning experience, motivation, knowledge acquisition, and skill development. However, despite the significant opportunity to use advanced learning analytics techniques to utilize the rich usage and navigation data provided by immersive virtual environments, the results of a comprehensive literature analysis [1] reveals that most educational research studies do not collect or analyze such data.

The work presented in this paper responds to the above critical needs and research gaps in today's engineering education landscape. Our findings have several important implications for engineering education. By showing the importance of time allocations within the simulated environment, our results can inform the design of such virtual environments. For example, a virtual field trip can be designed in a way that ensures students spend sufficient time observing the relevant aspects to enhance their experiential learning and perceived value of the virtual learning experience. By showing the relevance of age and personality traits, our findings indicate the potential to enhance individualized teaching and learning by tailoring the design of immersive virtual experiences based on such factors. By showing the effect of experience with computer simulations, our results indicate the potential to enhance the effectiveness of immersive virtual environments through prerequisite training sessions. Lastly, by showing the effect of past work experience, our findings suggest that the optimal design of virtual learning environments can vary for traditional student populations (that typically lack prior work experience) versus professional learners, continuing education, and workforce reskilling and upskilling. While traditional studies primarily focus on pre-/post-tests to assess learning via computer simulations and ignore learner interactions with the simulation (see [43] for example), our results add to the learning analytics literature [44] by showing the potential and value of recording students' actions within a simulated learning environment.

That said, due to the focus on a single subject matter and limited sample, care must be taken in interpreting and generalizing our findings. Additional experiments with a larger sample size would enhance the study's external validity. Future experiments could also expand the subject pool to include a more diverse group of learners (e.g., age groups). Our study involved undergraduate students from a particular course context (programming with Java). Further studies will be needed across various engineering disciplines, student populations (e.g., graduate and professional learners), and educational settings (e.g., online vs in-person). Another limitation of this work pertains to the use of surveys to measure experiential learning and self-assessment of learning outcomes. In general, self-reported measures are subjective and prone to biases. Future research could complement these results with other measures such as performance assessments and knowledge tests to strengthen the study's results. Future extensions could also involve quantifying other measures of navigation that take into account the viewing angle, speed of movements, and paths taken by the learner within the immersive simulated environment. The findings of such extensions will not only enhance our understanding of the role of navigation, but also help developers of immersive learning environments to optimize the design of *guided* virtual tours that involve prescribed navigation paths. Another rich avenue for future research involves quantifying and assessing other types of user-simulation interaction beyond navigation, such as interactions with static objects, interactive entities, and avatars of other users that are simultaneously present in the same immersive simulated environment. Other immersive technologies, such as Augment Reality (AR) [45], can be studied to see how learners' interactions with the virtual environment vary depending on the technology being used. Insights derived from future studies along the above lines will provide valuable information to enhance the design of immersive virtual environments and the forms of interaction needed to improve learning outcomes.

With the growing application of virtual simulated environments and immersive technologies in STEM education and workforce training, we hope that this paper and its future extensions will encourage more attention toward quantitative assessment and analysis of learner-simulation interactions and their impact on learning outcomes. To further facilitate future investigations by other educational researchers, we publicly share a set of ISBL modules related to various STEM topics on our project website [46].

7. Conclusions

In this paper, we implemented sample ISBL modules for teaching and learning object-oriented programming in a computer science course. ISBL provides a learning environment that enables students to interact and navigate through a virtual environment that mimics real-world situations. We screen recorded students' interactions and navigation in the virtual simulated environment and employed a video analytics tool that uses machine learning techniques to extract navigation statistics from students' screen recorded videos. We then performed multivariable regression analysis to investigate whether navigation-related factors can be predictors of students' learning outcomes. Regarding the first two research questions posed in Section 4, our statistical analysis indicated that two navigation-related measures, namely the total time spent in the virtual environment and deviation from the average distribution of time allocations across all participants (as measured by our *Stdev* factor), are significant statistical predictors of experiential learning and self-assessment of learning. Regarding the third research question, the results showed that a combination of the two navigation-related factors and learners' demographics (e.g., age), personality factors (e.g., active imagination and trusting), prior work experience, and past experience with computer simulations can be used to predict experiential learning and self-assessment of learning. It is worth noting that our results did not show a significant effect for gender and race in the context of ISBL.

Acknowledgements – This material is based upon work supported by the National Science Foundation under Grant No. 2000599. Any opinions, findings, and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. The preliminary stages of this work were supported by funds from the Office of the Executive Vice President and Provost at The Pennsylvania State University as part of the university's strategic seed grant program related to transforming education. We would also like to thank Aung Nay Htet Oo, an undergraduate researcher at Penn State University, who assisted in the development of the ISBL modules and associated simulation models used in this paper.

References

1. J. Radianti, T. A. Majchrzak, J. Fromm and I. Wohlgenannt, A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda, *Computers & Education*, **147**, p. 103778, 2020.
2. M. Brimble, Skills assessment using video analysis in a simulated environment: an evaluation, *Nursing Children and Young People*, **20**(7), pp. 26–31, 2008.
3. J. Parong and R. E. Mayer, Learning science in immersive virtual reality, *Journal of Educational Psychology*, **110**(6), pp. 785–797, 2018.
4. J. Chung and H. J. Gardner, Temporal presence variation in immersive computer games, *International Journal of Human-Computer Interaction*, **28**(8), pp. 511–529, 2012.
5. L. Plumanns, T. Sommer, K. Schuster, A. Richert and S. Jeschke, Investigating mixed-reality teaching and learning environments for future demands: The trainers' perspective, in S. Jeschke, I. Isenhardt and K. Henning (eds), *Automation, Communication and Cybernetics in Science and Engineering 2015/2016*, Cham, Springer International Publishing, p. 393, 2016.
6. S. J. Smith, S. L. Farra, D. L. Ulrich, E. Hodgson, S. Nicely and A. Mickle, Effectiveness of two varying levels of virtual reality simulation, *Nursing Education Perspectives*, **39**(6), pp. E10–E15, 2018.
7. J. Bermejo Berros and M. Gil Martínez, The relationships between the exploration of virtual space, its presence and entertainment in virtual reality, 360° and 2D, *Virtual Reality*, **25**, pp. 1–17, 2021.
8. C. H. Mowrey, P. J. Parikh and K. R. Gue, The impact of rack layout on visual experience in a retail store, *INFOR: Information Systems and Operational Research*, **57**(1), pp. 75–98, 2017.
9. K-H. Tai, J-C. Hong, C-R. Tsai, C-Z. Lin and Y-H. Hung, Virtual reality for car-detailing skill development: Learning outcomes of procedural accuracy and performance quality predicted by VR self-efficacy, VR using anxiety, VR learning interest and flow experience, *Computers & Education*, **182**, p. 104458, 2022.
10. D. Kamińska, G. Zwoliński and A. Laska-Leniewicz, Usability testing of virtual reality applications – The pilot study, *Sensors*, **22**(4), p. 1342, 2022.
11. P. Araiza-Alba, T. Keane, W. S. Chen and J. Kaufman, Immersive virtual reality as a tool to learn problem-solving skills, *Computers & Education*, **164**, p. 104121, 2021.
12. E. D. Innocenti, M. Geronazzo, D. Vescovi, R. Nordahl, S. Serafin, L. A. Ludovico and F. Avanzini, Mobile virtual reality for musical genre learning in primary education, *Computers & Education*, **139**, pp. 102–117, 2019.
13. J. Calvert and R. Abadia, Impact of immersing university and high school students in educational linear narratives using virtual reality technology, *Computers & Education*, **159**, p. 104005, 2020.
14. M. Nowparvar, X. Chen, O. Ashour, S. G. Ozden and A. Negahban, Combining immersive technologies and problem-based learning in engineering education: Bibliometric analysis and literature review, *Proceedings of the 2021 ASEE Annual Conference and Exposition*, Online/Virtual Meeting, July 26–29, 2021.
15. A. Negahban, Simulation in engineering education: The transition from physical experimentation to digital immersive simulated environments, *Simulation*, **100**(7), pp. 695–708, 2024.
16. D. H. Jonassen, Objectivism versus constructivism: Do we need a new philosophical paradigm?, *Educational Technology Research and Development*, **39**(3), pp. 5–14, 1991.
17. R. C. Anderson, The notion of schemata and the educational enterprise: General discussion of the conference, in R. C. Anderson, R. J. Spiro and W. E. Montague (eds), *Schooling and the Acquisition of Knowledge*, Routledge, London, p. 415, 1977.
18. M. Albanese, Problem-based learning: Why curricula are likely to show little effect on knowledge and clinical skills, *Medical Education*, **34**(9), pp. 729–738, 2000.
19. S. B. Merriam, Andragogy and self-directed learning: Pillars of adult learning theory, *New Directions for Adult and Continuing Education*, **89**, pp. 3–14, 2001.
20. M. Nowparvar, O. Ashour, S. G. Ozden, D. Knight, P. Delgoshaei and A. Negahban, An assessment of simulation-based learning modules in an undergraduate engineering economy course, *Proceedings of the 2022 ASEE Annual Conference and Exposition*, Minneapolis, Minnesota, June 26–29, 2022.

21. S. G. Ozden, A. Negahban, O. Ashour and D. Knight, Investigating the impact of context choice on learning experience via immersive simulations in an object-oriented programming course, *Proceedings of the 2023 ASEE Annual Conference and Exposition*, Baltimore, Maryland, June 26–29, 2023.
22. O. Ashour, S. G. Ozden and A. Negahban, Analyzing immersive simulation-based learning modules in remote and in-person settings, *Proceedings of the 2024 ASEE Annual Conference and Exposition*, Portland, Oregon, June 23–26, 2024.
23. S. G. Ozden, O. Ashour and A. Negahban, Novel immersive simulation-based learning modules for teaching fundamental database concepts, *Proceedings of the 2020 ASEE Annual Conference and Exposition*, Online/Virtual Meeting, June 22–26, 2020.
24. M. L. Smith, D. Hamplová, J. Kelley and M. D. R. Evans, Concise survey measures for the Big Five personality traits, *Research in Social Stratification and Mobility*, **73**, p. 100595, 2019.
25. D. A. Kolb, *Experiential Learning: Experience as the Source of Learning and Development*, Pearson Education Inc., Upper Saddle River, New Jersey, 2015.
26. T. Danko, Student perceptions in homeland security and emergency management education: Experiential learning survey, *Journal of Experiential Education*, **42**(4), pp. 417–427, 2019.
27. S. Alaoutinen and K. Smolander, Student self-assessment in a programming course using Bloom's revised taxonomy, *Proceedings of the Fifteenth Annual Conference on Innovation and Technology in Computer Science Education*, pp. 155–159, 2010.
28. T. J. Lasley, Bloom's taxonomy, in T. C. Hunt, J. C. Carper, T. J. Lasley and C. D. Raisch (eds), *Encyclopedia of Educational Reform and Dissent*. SAGE Publications Inc., Thousand Oaks, California, p. 107, 2010.
29. N. Soriano, A. Negahban, S. G. Ozden and O. Ashour, An open source video analytics tool for analyzing learner navigation in immersive simulated environments, *Proceedings of the 2023 Annual Modeling and Simulation Conference*, Hamilton, ON, Canada, May 23–26, pp. 472–483, 2023.
30. A. G. Sisselman-Borgia and G. C. Torino, Innovations in experiential learning for adult learners. *Journal of Applied Learning in Higher Education*, **7**, pp. 3–13, 2017.
31. K. Cercone, Characteristics of adult learners with implications for online learning design. *AACE Journal*, **16**(2), pp. 137–159, 2008.
32. T. Hailikari, N. Katajavuori and S. Lindblom-Ylanne, The relevance of prior knowledge in learning and instructional design. *American Journal of Pharmaceutical Education*, **72**(5), pp. 113–121, 2008.
33. V. Terzis, C. N. Moridis and A. A. Economides, How student's personality traits affect computer-based assessment acceptance: Integrating BFI with CBAAM, *Computers in Human Behavior*, **28**(5), pp. 1985–1996, 2012.
34. J. Meyer, T. Jansen, N. Hübner and O. Lüdtke, Disentangling the association between the Big Five personality traits and student achievement: Meta-analytic evidence on the role of domain specificity and achievement measures, *Educational Psychology Review*, **35**(12), pp. 1–34, 2023.
35. L. Bayerlein, The impact of prior work-experience on student learning outcomes in simulated internships, *Journal of University Teaching and Learning Practice*, **17**(4), pp. 44–61, 2020.
36. C. Liang, Y. Hsu, Y. Huang and S-C. Chen, How learning environments can stimulate student imagination, *Turkish Online Journal of Educational Technology*, **11**(4), pp. 432–441, 2012.
37. N. A. Bowman and P. L. Hill, Measuring how college affects students: Social desirability and other potential biases in college student self-reported gains, *New Directions for Institutional Research*, **2011**(150), pp. 73–85, 2011.
38. B. Dumfart and A. C. Neubauer, Conscientiousness is the most powerful noncognitive predictor of school achievement in adolescents, *Journal of Individual Differences*, **37**(1), pp. 8–15, 2016.
39. J. Meyer, J. Fleckenstein, J. Retelsdorf and O. Köller, The relationship of personality traits and different measures of domain-specific achievement in upper secondary education, *Learning and Individual Differences*, **69**, pp. 45–59, 2019.
40. H. C. Pham, N-N. Dao, A. Pedro, Q. T. Le, R. Hussain, S. Cho and C. Park, Virtual field trip for mobile construction safety education using 360-degree panoramic virtual reality, *International Journal of Engineering Education*, **34**(4), pp. 1174–1191, 2018.
41. A. U. Yerden and N. Akkus, Virtual reality remote access laboratory for teaching programmable logic controller topics, *International Journal of Engineering Education*, **36**(5), pp. 1708–1721, 2020.
42. K. Cook-Chennault and A. Farooq, A validated assessment tool: Students' perceived value of engineering laboratories in a virtual environment, *International Journal of Engineering Education*, **39**(4), pp. 860–876, 2023.
43. J. J. Galán-Díaz, S. F. Garrido, A. I. García-Diez, M. A. Graña-López, A. Filgueira-Vizoso, and L. Castro-Santos, Assessment of engineering undergraduates active learning experience using computer simulations, *International Journal of Engineering Education*, **40**(2), pp. 358–367, 2024.
44. C. N. Tulha, M. A. G. De Carvalho and L. N. De Castro, Application of learning analytics in a remote lab context: A systematic literature review, *International Journal of Engineering Education*, **38**(5), pp. 1340–1353, 2022.
45. E. J. Estadt, H. Nguyen, K. S. Stuart, J. Delva, A. Negahban, O. Ashour and S. G. Ozden, Warehouse augmented reality program (WARP): A web tool for warehouse design and operation education, *Proceedings of the 2024 ASEE Annual Conference and Exposition*, Portland, Oregon, June 23–26, 2024.
46. Immersive Simulation-Based Learning (I-SBL), https://sites.psu.edu/immersivesimulationpbl, Accessed 15 April 2024.

Mahgol Nowparvar received her MSc in Data Analytics from the Great Valley School of Graduate Professional Studies at The Pennsylvania State University in 2022 and a BS degree in Applied Mathematics from University of Wisconsin in 2020.

Noah Soriano is a graduate research assistant and an MS student in the College of IST at The Pennsylvania State University, University Park. He earned his BS in Computational Data Science from Penn State. His research interests include machine learning design and application to computer vision. His e-mail address is nfs5267@psu.edu.

Sabahattin G. Ozden is an Associate Professor of Information Technology and Technology at Penn State Abington. He received BS degree in Software Engineering with a double major in Industrial Systems Engineering from Izmir University of Economics in 2009. He received his Master of Industrial and Systems Engineering and the PhD degree in Industrial and

Systems Engineering from Auburn University in 2012 and 2017, respectively. His research interests are warehousing, optimization, and information systems. He can be reached at gokhan@psu.edu and http://gokhanozden.com.

Parhum Delgoshaei is an Assistant Teaching Professor of Systems Engineering at The Pennsylvania State University, Great Valley School of Graduate Professional Studies. He received his BS in electrical engineering from University of Tehran, his MS in electrical engineering from Western Michigan University, and his PhD in Engineering Education from Virginia Tech. His research interests include design of hybrid microgrids utilizing renewable and combined heat and power and sources, design and implementation of smart energy systems, and deterministic and stochastic optimization of distributed energy resources deployed within microgrids. He has developed information infrastructures for remote labs to support education for microgrids, distributed energy resources, energy efficiency, and battery energy storage systems at the residential and commercial building scales. He has developed and taught graduate courses in distributed energy planning and management and commercial solar electric systems, and undergraduate courses in photovoltaic systems design and construction and building energy efficiency.

Omar Ashour is a Professor of Industrial Engineering at Pennsylvania State University, The Behrend College. Dr. Ashour received a BS degree in Industrial Engineering/Manufacturing Engineering and an MS degree in Industrial Engineering from Jordan University of Science and Technology (JUST) in 2005 and 2007, respectively. He received his MEng degree in Industrial Engineering/Human Factors and Ergonomics and a PhD degree in Industrial Engineering and Operations Research from The Pennsylvania State University (PSU) in 2010 and 2012, respectively. Dr. Ashour was the inaugural recipient of William and Wendy Korb Early Career Professorship in Industrial Engineering in 2016. Dr. Ashour's research areas include data-driven decision-making, modeling and simulation, data analytics, immersive technologies, and process improvement. He contributed to research directed to improve design and engineering education. Dr. Ashour currently serves as a Technical Vice President (TVP) on the Technical Operations Board (TOB) of the Institute of Industrial and Systems Engineers (IISE).

Ashkan Negahban is an Associate Professor of Engineering Management at The Pennsylvania State University, Great Valley School of Graduate Professional Studies. He received his PhD and master's degrees from Auburn University (USA) and his BS from University of Tehran (all in Industrial and Systems Engineering). His research involves stochastic simulation methods, primarily agent-based and discrete-event simulation. He also conducts research related to novel simulation-based learning environments in STEM education. His email and web addresses are aun85@psu.edu and https://ashkannegahban.com.