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A Validated Assessment Tool: Students' Perceived Value of Engineering Laboratories in a Virtual Environment*

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Experimental laboratories are required for all engineering disciplines to fulfill undergraduate degree requirements. These capstone laboratories are designed to reinforce fundamental science, technology, engineering, and mathematical content associated with core aspects of the discipline. These laboratories are usually physical experiments; however, the emergence of online degrees, the COVID pandemic, and the development of virtual lab technologies have expanded how students experience capstone labs. An instrument is needed to measure the relationship between students' engineering role identity, technology acceptance, and prior learning experiences. This study reports the development and validation of a Student Perceived Value of an Engineering Laboratory (SPVEL) assessment instrument for capstone mechanical and aerospace engineering laboratories. The items for the SPVEL assessment instrument were constructed according to three theoretical models: The Technology Acceptance Model (TAM), Inputs-Environment-Outcome (IEO) Conceptual Model, and Engineering Role Identity (ERI). An exploratory load factor analysis was conducted on responses to thirty-five questionnaire items to discover the underlying factor structure of the dataset. Squared multiple correlations were used as prior communality estimates, and the principal axis factoring method was employed to extract the factors. The study was conducted in a capstone senior Mechanical and Aerospace engineering laboratory course at a university in the northeastern United States with 227 undergraduate participants. Six factors were extracted, and Cronbach's alpha for data reliability was found to be 0.86 for the set of thirty-five questions and within the range of 0.67 to 0.94 for all six factors. Thus, this SPVEL assessment tool had high internal consistency of reliability coefficients. The SPVEL Assessment tool provides a mechanism for observing how students interact with and experience engineering laboratories. The relationships between students' ability to leverage prior experiences and learn from the laboratory experience, prepare for their roles as engineering professionals, and accept innovative technologies used for teaching engineering education are also forms of information gleaned from this tool. Using the SPVEL assessment instrument could enhance the literature on evaluating the effectiveness of undergraduate engineering laboratories and facilitate the improvement of laboratory design in undergraduate mechanical and aerospace engineering laboratory environments.

Keywords: assessment tool; instrument validation; engineering laboratory; technology acceptance model; engineering role identity; I-E-O conceptual model

1. Introduction – Engineering Undergraduate Labs

1.1 A Historical Context of Engineering Labs

Instructional laboratories have been an integral part of the undergraduate engineering curriculum in varying degrees throughout the history of the engineering profession. In fact, since the founding of the engineering discipline at the U.S. Military Academy at West Point, NY, in 1802, instructional laboratories have been the foundation of undergraduate engineering education. These instructional laboratories were often coupled with fieldwork, drafting, mathematics, and science. This format of training persisted throughout the middle and nineteenth centuries as more engineering schools, e.g., Yale (1852), MIT (1865), Union College (1845), Cornell (1830), etc., emerged [1, 2] and built physical infrastructures to house engineering laboratories to align with realistic work environments. This form of instruction continued until the end of World War II, when it was discovered that scientists, rather than engineers developed the majority of inventions during the war. This discovery led to the publishing of the Grinter Report [3] by the American Society of Engineering Education (ASEE) that called for strengthening the requirements for engineers in basic sciences, mathematics, chemistry, and physics. The reason for this modification of the course curriculum for engineers was due to the production of engineers who were too "practically oriented," i.e., not well-equipped to solve engineering problems using first principles. The increase in theoretical curriculum led to the establishment of two distinct disciplines: engineering technologists and engineers, whose course curriculum was regulated by the Engineers' Council for Professional Development, which was the precursor to the Accreditation Board for Engineering and Technology (ABET) [4]. The focus on the inclusion of theoretical concepts in the engineering curriculum and diminished investment in instruction labs led to the graduation of many engineers with little practical or laboratory experience. During this time

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there was also a growing confusion between the roles of technologists and engineers, where many technologists filled the roles and assumed the title of engineers. To address this confusion, engineering organizations were reorganized, and ABET was formed. It was then concluded that the engineering curriculum at that time was not preparing students with laboratory practice. Since then, ASEE has produced a number of reports affirming the importance of laboratory instruction for undergraduate curriculum, along with recommendations for best practices, e.g., reports in 1967, 1986, 1987, etc. [2, 5].

Presently, the inclusion of laboratory instruction within engineering disciplines continues to be a necessary component within the undergraduate curriculum, however providing students with high quality laboratory experiences remains a challenge due to several factors. First, as the complexity of instrumentation and software increases, so do the infrastructural and facilities, maintenance, and specialized operation support (technicians). Second, many scholars argue that changes in faculty reward and recognition systems at universities, which were originally geared toward development of engineering education tools and pedagogy has been replaced with a system that recognizes and rewards individual research programs that siphon off time, support, and resources from time-intensive work on instructional labs. Third, the integration of computing and online technologies has provided opportunities for new ways for engaging students in engineering laboratories, i.e., virtual and hybrid laboratories. However, the best practices and ways of assessing these new forms of laboratories is still an area that is underdeveloped.

The role that instructional labs play in the development of engineers becomes more critical as these labs reaffirm theoretical foundational coursework and can also provide a meaningful link to aspects of the engineering profession. Cultivating students' authentic knowledge of the engineering profession is important as it has been found that many undergraduate engineering students have higher self-proclaimed levels of professional engineering identity than their developmental levels actually are [6]. Further, the literature suggests that students' misunderstanding of the scope and work of 21st century engineers during their formal education and sustained misalignment of their perceptions of the future engineering profession may lead to students' disengagement or withdrawal from engineering preparation programs and the profession [6]. Thus, development of assessment tools for 21st century labs that reflect and evaluate students' perceptions of the engineering field, their identity, and learning are needed to advance the effectiveness of engineering instructional labs, which can often utilize physical, online, virtual, and simulation technologies [6–11]. This work focuses on the validation of an instrument that was designed to evaluate and assess online instructional virtual engineering laboratories.

Using the responses from 227 undergraduate mechanical and aerospace engineering students, an Exploratory Factor Analysis (EFA) was performed on the questionnaire to validate it as an assessment instrument for undergraduate engineering laboratories. The work also builds upon another study of assessment of in-person and virtual labs [12] which provided evidence that a traditional course evaluation instrument generally lacked meaningful information about students' experiences of the laboratory environment. The questionnaire used in this study was used as a feedback mechanism for a mechanical and aerospace engineering virtual lab that took place in the School of Engineering at a university located in the Northeastern region of the United States. This study was also approved by a university internal review board (IRB) for students to participate in a multiple year study about their experiences participating in a laboratory comprising labs that covered multiple topics over an academic year. The purpose of this study is to validate this questionnaire, so that the instrument can be used by laboratory instructors and researchers to garner students' perceptions of effectiveness of virtual and in-person laboratories taken as part of the engineering curriculum.

2. Virtual Engineering Laboratories – What are They?

Online learning modules and virtual laboratory (VL) platforms have been designed, developed, and studied as tools in many classrooms for several decades to enhance student engagement and academic performance in K-12, undergraduate (UG) and graduate (GR) populations. There has been a great deal of research on VLs in science, technology, engineering, and mathematics (STEM) disciplines in UG classrooms, e.g., in biology [13, 14], chemistry [15, 16], physics [17], computer science [15, 18], general engineering [19, 20], software and electrical engineering [18, 21–33], mechanical engineering (ME) [34–42], chemical engineering [43, 44], computer aided design [45], power engineering [46, 47], biomedical [48, 49] engineering, and aerospace engineering [50].

Virtual laboratories use media formats to simulate physical laboratories that are traditionally designed for learners who participate in in-person laboratory settings. Virtual and remote laboratories are often categorized in two ways. One way is where real laboratory experiments are computer simulated and accessed online. The other type of virtual lab is one that allows the user to remotely access, control, operate, and/or observe the operation of equipment, computers, and data capture through the internet. The objective of most virtual lab technologies is to provide an opportunity for the user to perform or observe experiments without being in the physical lab environment. The ways in which these virtual and remote learning environments and tools are used varies. For example, VLs have been used to supplement traditional course materials in large-scale lecture classes or distance learning courses, to enhance lecture demonstrations, to prepare students for in-person action-oriented labs prior to engaging in the physical lab, to replace in-person labs, and to assess the performance of a student's ability to operate equipment and apply theoretical knowledge in performing practical tasks, e.g., [13, 49, 51, 52]. VLs have also been used to visualize complex physical phenomenon, such as, thermodynamic cycles and energy conversion systems, to optimize design efficiency and output [53]. Due to the variability in the ways in which these VLs have been used and studied; a myriad of methods has been used to evaluate their effectiveness, e.g., student outcomes (skills required for the Accreditation Board for Engineering and Technology), assessment of educational value as a function students' perceived motivation to learn, and students' *acceptance of new technologies* (ease of use and usefulness, i.e., the Technology Acceptance Model).

Many scholars who have evaluated VL effectiveness using metrics defined by the Accreditation Board for Engineering and Technology (ABET). For example, in a mechanical engineering course, [54] supplemented the traditional course materials (lecture and physical lab) with a learning module that included simulated VLs. These VLs were used to enhance students' engineering intuition towards predicting material testing results. In this work, students were also exposed to VLs to design and simulation software that illustrated research and industry settings. The curricular intervention was assessed quantitatively using a questionnaire (Likert-scale) and open-ended comments from the students. The effectiveness of the VL intervention was evaluated according to students' perceptions of the VL's *usefulness towards learning mechanical engineering concepts and simulation skills* and *the VL's ability to help them develop skills for employment* [54]. The effectiveness of the VL was also evaluated using the ABET Criterion 3 outcomes 1, 3, and 6 [4]. They also concluded that VLs enhanced students' interest in the subject matter due to the visual attractiveness of the simulation results, and also because they allow students to engage in more complex experiments than they could perform in a physical environment. They also found that VLs helped students to develop critical thinking skills by connecting multiple learning schema, theoretical knowledge, experimentation, and simulation.

Other researchers have used ABET criterion to evaluate student outcomes after being exposed to simulation VLs such as [55], who had students model dynamic systems and controls. Similarly, [56] incorporated virtual and remote labs as supplemental materials in an industrial automation course and used a KIPPAS (Knowledge and understanding, Inquiry skills, Practical skills, Perception, Analytical skills and Social and scientific communication) framework, which affirms criterion 3 in ABET. They concluded VLs had several advantages in comparison to traditional physical labs. VLs are cost effective and can provide multiple students access for participation. VLs also can facilitate scalability of classes that range from small to large in number of students. VLs also allow students to model scientific phenomena that are difficult to visualize in a physical environment, which enables the experiments performed to be adaptable for diversity of cognitive level, while at the same time maintaining a safe environment for learning. Thus, [56] concluded that VLs may also encourage student experimentation as multiple attempts can be made with no penalty or concern of breaking equipment, which may lead to reductions in time students spend learning. They also concluded that the use of VLs as supplemental tools motivated students to learn more and established a meaningful link between classroom activities and skills needed for future employers. As the aforementioned studies focused on evaluating labs using ABET metrics and student perceptions, others have used pre- and post-content assessments, e.g., [52, 57].

Several studies have used virtual labs to replace in-person labs and compared the effectiveness of both experiences according to students' pre- and post-content assessments where findings have varied. For instance, [52] studied the differences between a physical in-person lab and virtual lab using the Science Process Skill mastery pre- and post-tests for a 4th grade chemistry course. They found that students achieved higher scores when they engaged in the in-person labs but, the greatest difference between in-person and virtual lab scores was seen for girls in comparison to boys. Specifically, boys achieved higher content proficiency scores than the girls when participating in VLs. Conversely, researchers such as [58] conducted a study of student learning outcomes and preferences for several different lab formats, e.g., traditional in-person action oriented labs, remotely operated labs and simulated labs in an undergraduate engineering class. They concluded that in some instances students received higher scores in remote laboratories, while in others, there was no significant difference between performance in different laboratory formats. However, while students recognized the value in remote and simulated labs, such as technology-enabled formats, they still preferred in-person labs. Additionally, students' perception of their learning experience have more cognitive impact on them than the actual content or psychomotor means associated with the learning activity [59]. Hence understanding how students perceive benefits and deficits of learning environments is vital. Hence, many scholars have used the Technology Acceptance Model to elucidate how people associate the value of various forms of technology within a learning or working environment.

3. Theoretical Frameworks and Review of the Literature for Questionnaire Development

3.1 Technology Acceptance Model

The Technology Acceptance Model (TAM), developed by Davis [60, 61], posits that peoples' adoption of information technological systems is connected to and a function of two primary elements: users' *perceived usefulness* and the *perceived ease of use* of the technological system. In other words, people will use or not use an application/tool to the degree that they deem the tool will help them *do* their jobs better [60]. According to the TAM, if people believe the effort required to use a tool is too high or consider the benefits of its use less than the effort of use, they will abandon the use of the technology. Several studies have used the TAM to explore students' decisions to use VLs [62–64]. Most researchers assert that the TAM is most effective when other variables are considered. For example, [63] *concluded that undergraduates (UGs) chose to engage with VLs based on their ease of use, perceived usefulness, in addition to their prior knowledge* of materials related to the VLs. [63] also concluded that UGs with more prior experience achieved better grades in the course that incorporated VLs and associated higher value to the use of VLs, than those who did not have similar prior knowledge. Likewise, [64] used the TAM to examine students' acceptance of VLs and interactive activities. They concluded that *perceived efficiency, expectation, and satisfaction* were crucial factors to consider when using the TAM. Also, it has been found that undergraduate engineering students associate more value, i.e., usefulness from educational technologies that allow them to connect their real world experiences and theoretical knowledge to their perceptions of the real world engineering profession [65].

3.2 Inputs-Environment-Outcome (IEO) Conceptual Model

The majority of the literature that uses the Inputs-Environment-Outcome (IEO) conceptual model has focused on the examination of student success as a function of input variables such as learning disabilities [66, 67], amount and quality of time of involvement [68], perceived academic ability and drive to achieve [69], in UG and postsecondary level students. The IEO model has also been used to investigate the role of gender and race in the prediction of gender-role traditionalism [70], feminist identity and program characteristic roles in social advocacy [71] and differences in transition of black and white students from high school (HS) to college [72]. Less than a handful of workers have used the IEO model to assess outcomes in engineering, though the engineering community is beginning to understand the importance of considering student inputs and environment as described by the IEO model in assessment of engineering curriculum. For example, van den Broeck, et al. [73] used the IEO model to explore differences in dropout and academic achievement of *traditional* versus *lateral entrance* students in the SoE at Katholieke Universiteit Leuven in Belgium, where input variables were prior education and study patterns. They concluded that both groups had similar drop-out rates and academic achievement, which they attributed to mandatory curriculum course work required for lateral (bridged) students to enter the program [73].

3.3 Engineering Role Identity

Engineering role identity describes how students form their identities in the engineering role based on their experiences working in a community of practice and in the college environment. Godwin and Kirn [74] defined engineering role identity as how students describe themselves and are positioned by others into the role of an engineer. Role identity is premised on three elements. First, students' identity development is dialogic [75], i.e., based on a social perspective of communication. Second, students' identity is connected to their interest in the subject and beliefs about their competence relating to the subject [76, 77], which both **influence their motivation to persist in and learn about the subject**. Third, engineering role identity depends on one's comprehension of concepts, and ability to connect new knowledge to prior information [78, 79] (cognitive learning perspective). Many studies have shown engineering identity as a predictor of students' educational and professional persistence. Most of these studies have focused on how students' perception of their engineering role identity is related to their culture and enacting the qualities, they believe are required for being an engineer [80, 81]. In the context of developing an instrument that considers students' identity while introducing a virtual learning environment, students' role identity could play a meaningful role. This is because students' role identity focuses on the ways students describe themselves and their experiences with engineering games, how they value the game in their learning, and how they understand engineering concepts as they engage in the virtual learning environment. This is supported by several engineering identity theorists' assertion that engineering identity is a function of one's national affiliation within a cultural context [82–84], and the importance of students seeing themselves as one who can "do" or "be" an engineer to persist in the profession [80, 81, 85].

Understanding the interrelationship between one's identity and their persistence in the STEM educational process and formation into an engineer has been a subject of many researchers over several decades, where differences between subgroups (race, gender, socioeconomic, sexuality, etc.) and the traditional stereotypical white/Asian masculine culture of engineering have been noted [86, 87]. For example, researchers [80, 81] used the social identity theory described by [88, 89] to understand how students identify as engineers as a function of gender. It was found that there are significant gender differences in how first-year students identify with engineering and becoming an engineer, where fewer women were exposed to the engineering field through applied or building experiences (0% women to 26% men); interactions with relatives who were engineers (20% women to 26% men) and STEM activities (10% women to 26% men) [81].

4. Experimental Method

4.1 Research Environment and Experimental Method

A Mixed-Method Convergent Research Design Method [90] was proposed and approved by the primary Institutional Review Board of the first author. The study took place at a Research-1 [91], research-intensive institution in the Northeastern region of the United States. The data described herein represents phases of a multi-year study (2020–2022). Participants in the study (N = 304) were recruited to participate from a mechanical and aerospace undergraduate engineering laboratory course that took place in the 2020–2021 academic school year, while the laboratory was offered virtually during the COVID-19 pandemic.

4.2 Data Collection Protocol

Students who participated in this study were all undergraduate engineering students who were enrolled in a mechanical and aerospace engineering laboratory. The remote labs were designed to mimic the experience of being in the physical demonstration lab. Three hundred and four students participated in the study by submitting responses to a pre-lab and a post-lab questionnaire. Seventy-seven of the participants neglected to complete either the pre- or the post-lab. So, the minimum number of responses for each question is 227.

Due to the large number of students enrolled in the course, students were divided into multiple sections and were rotated to different labs that occurred simultaneously through the course semester. Students participated in one introductory laboratory lecture that discussed course objectives, design, and expectations. Before engaging in or with any laboratory activities students were asked to complete a pre-lab questionnaire with the questions that are detailed in Table 5. After finishing the pre-lab questionnaire, students downloaded and observed a pre-recorded video lecture that described the theoretical concepts covered in each lab. These recorded lectures were created by instructors who taught the theory associated in the lab in the technical courses. These technical courses were pre-requisites to the senior educational engineering lab. Students were also provided equipment manuals and laboratory guides for each lab prior to beginning the lab.

In the virtual laboratories, students observed the teaching assistant (TA) conduct the lab synchronously via multiple video feeds while logged on to a video conference platform. A schematic of the virtual lab set up is provided in Fig. 1. As shown in this figure, several cameras focused on specific aspects of the equipment where inputs were provided, and where data was captured as output. Students observed the operation of the equipment synchronously as the TA directed the lab procedures. In some cases, TA's asked students to indicate the steps in the procedure and/or express parameters for operation.

Over the course of the semester of the study, students participated in five virtual labs: LabVIEW, Material Testing, Momentum Deficit, Steam Engine, and Vibrations. These laboratories were based on fundamental theoretical content covered in courses that the majority of students took prior to the engineering lab as prerequisites. Students were given two weeks to submit a laboratory report after participating in the lab. Students were prompted to complete a post-lab questionnaire after each lab with the questions detailed in Table 6.

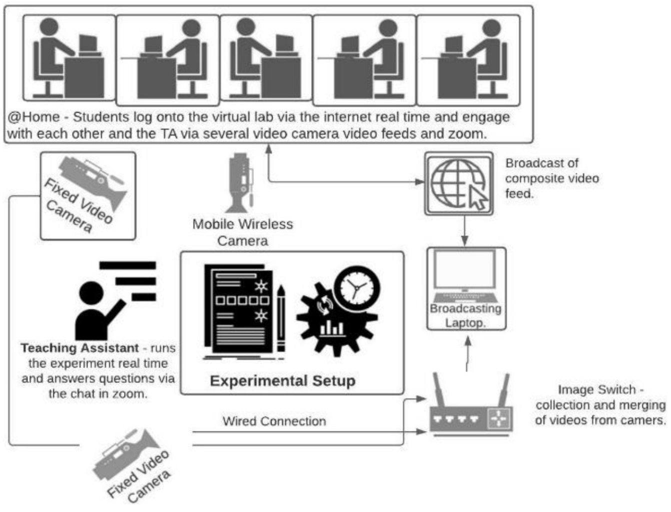

Fig. 1. Illustration of the virtual laboratory experimental setup for the study.

5. Questionnaire Development – Validation Methods

A multiple item questionnaire was created for this project called the Student Perceived Value of an Engineering Laboratory (SPVEL) assessment. This questionnaire was designed to leverage three theoretical models, i.e., the Technology Acceptance Model [60, 61], Inputs-Environment-Outcome (IEO) Conceptual Model [68, 92], and Engineering Role Identity [74, 77, 93]. The original draft of the questionnaire (prior to the application of the load factor analysis) comprised 35 items as shown in the Appendix in Table 5 and Table 6, which depict portions of the questionnaire administered pre- and post-lab, respectively. Twenty-seven (27) of the items were rated on a Likert-type scale that ranged from 1 to 5, where 1, 2, 3, 4, and 5, referred to "Strongly Disagree", "Somewhat Disagree", "Neither agree nor Disagree", "Somewhat Agree", and "Strongly Agree", respectively. The other items in the questionnaire, were scaled according to number of occurrences/experiences and hours of participation.

The process for validating the SPVEL instrument consisted of four steps in chronological order [94]: (1) determination of Cronbach's Alpha for the entire questionnaire, (2) exploratory load factor analysis using the principal axis method, (3) the principal component analysis (PCA) for the reduction approach, and (4) determination of Cronbach's Alpha for each of the factors derived from the reduction method.

5.1 Cronbach's Alpha Reliability Method

The reliability of the entire questionnaire and subsequent factor loadings was assessed via Cronbach's Alpha (α) to ascertain the strength of the consistency in the questionnaire and loadings for measuring the concepts detailed Table 5 and Table 6. To interpret Cronbach's Alpha a score between 0.7–0.95 is generally considered very high and demonstrates that the items within the questionnaire of a loading factor possess high test-retest reliability and internal consistency (connected to the inter-relatedness of the items in the test). While Cronbach Alpha scores between 0.55 and 0.70 are considered acceptable, those that are less than 0.55 are not [95, 96]. A Cronbach alpha score that is less than 0.55 could indicate an inappropriately low number of questions, which could be due to two common issues: (a) low number of questions and hence poor inter-relatedness between the items and (b) multiple-choice questions that have only two or three choices of responses generally have lower reliability score compared to Likert style questions that have five to seven response choices [96].

5.2 Principal Axis Factoring Method – Exploratory Load Factor Analysis

An exploratory factor analysis was conducted to investigate the factor structure underlying the responses to a questionnaire that comprised 35 items. Principal axis factoring was used to extract the factors, and the squared multiple correlations were used as prior communality estimates. A Kaiser-Meyer-Olkin (KMO) test was also performed to validate that an appropriate number of sampling sizes were used in the study. In particular, this statistic (ranges from 0.0 to 1.0) was used to measure the proportion of variance among variables that may be common variance, which determines if the data is suitable for factor analysis, where values greater than or equal to 0.7 indicate suitable data [97]. A Barlett's test for sphericity was performed to determine whether the data has an

Table 1. The racial and ethnic demographics of the undergraduate mechanical and aerospace engineering (MAE) student participants in this study

Race/Ethnicity	**Number**	**Percent**
White, Non-Latino (Not Hispanic)	118	39%
Black or African American, Non-Latino (Not Hispanic)	19	6%
Asian	92	30%
Two or more races and/or ethnicities	7	2%
Prefer not to answer	10	3%
White, Latino (Hispanic)	19	6%
Black or African American, Latino (Hispanic)	2	1%
LatinX (Latin American origin or descent)	16	5%
Middle Eastern, North African	21	7%
Total Responses	**304**	**100%**

adequate number of correlations. In other words, this test was conducted to check for redundancy between variables, where a value of less than or equal to 0.05 indicates that the correlation matrix is not the identity matrix [97]. Finally, a scree plot containing the eigenvalues of the factors arranged in descending order of magnitude was used to ascertain the most meaningful factors of the structure [94].

5.3 Principal Component Analysis (PCA) Method

Principal Component Analysis (PCA) is the dimensionality-reduction method that was used to reduce the dimensions of the large data set to make a predictive model. In this way, each item is projected onto the first few principal components to obtain lower-dimensional data, while maintaining the majority of the data's variation.

6. Results

6.1 Demographics of the Participants

The racial and ethnic demographics of the students who participated in this study are provided in Table 1 and Table 2. The demographics of the student population presented in this table demonstrate that the racial and ethnic groups are similar in percentage to the national averages recorded by the ASEE (Engineering By the Numbers report [98]). For example, 15% of the students have identified themselves as women in this study, which is close to the national average values for mechanical engineering (16.5%) women graduates. Similarly, the percentage of LatinX participants in this study, e.g., 12%, is close to the percentage of graduating students nationally for all engineering majors, i.e., 13.1%. Lastly, the number of Black/African American participants, e.g., 6%, supersedes the national average values for all engineering majors (4.5%).

Table 2. The gender demographics of the undergraduate MAE participants in this study

Gender	**Frequency**	**Percent**
Male	232	76%
Female	47	15%
Prefer not to answer	25	8%
Total	**304**	**100%**

6.2 Analysis of Data Reliability of the 35-Item Questionnaire – Cronbach's Alpha Reliability Method

The analysis of the data initiated by ascertaining the reliability of the entire questionnaire via Cronbach's Alpha (α) to ascertain the strength of the consistency in the questionnaire. Cronbach Alpha was computed for the pre- and post-lab questions independently, and for the combined questionnaire. As anticipated, the Cronbach's alpha scores for the pre-lab, post-lab, and combined questionnaires were 0.464, 0.933, and 0.858, respectively. The low alpha score for the pre-lab questionnaire questions has to do with the scale and number of questions used. As shown in Table 5 and Table 6, Q1–Q7 were not based on a Likert-type point scale, and instead were based on the frequency of occurrences, where Q1–Q5 had 3 choices and Q6 and Q7 had 5 choices. On the other hand, the remaining questions, e.g., Q8–Q35 were based on a 5-point Likert-scale for each item. In the pre-lab questionnaire, the majority of the questions had a maximum of three choices. This small number of choices makes it difficult for the SPSS software to conduct a valid reliability analysis for these questions. However, the questions that did have a 5-point Likert Scale had high reliability, i.e., greater than 0.67, i.e., Q6–Q15. The post-lab questions were all posed on a 5-point Likert scale and has a high alpha score of 0.933, which suggests a high internal consistency of the data. Although the individual alpha score for the pre-questionnaire was low, when combined with the post-questionnaire, the combined alpha value goes to 0.858. This provides sufficient evidence that the test-retest reliability of the combined questionnaire is remarkably high, and the internal consistency of the items are high as well.

6.3 Exploratory Factor Analysis

An Exploratory Factor Analysis (EFA) was conducted to investigate the factor structure underlying the responses to the questionnaire that comprised thirty-five items as detailed in Table 1 and Table 2. The descriptive statistics for the pre- and post-lab questions, i.e., the mean and standard deviations for each of the responses are provided in the table. A normality test was conducted for each item in the questionnaire that combined the pre- and post-lab questions. From the normality test, it was determined that the distribution of the responses was skewed and did not follow a normal distribution. Hence, a maximum likelihood estimator (used for normal distribution responses) was not used for estimating parameters. Instead, the data was treated as categorical data, which are ordered and non-normal [94].

The factor structure of the latent variables was estimated with the aid of SPSS software where squared multiple correlations were used as prior communality estimates. Polychoric correlation factors were calculated from the 35 original categorical variables [99]. This correlation matrix indicated that both positive and negative correlations existed in the data, where the correlation values ranged from –0.006 to 0.525. The range of the correlation coefficients indicated that the putative factors from the EFA were not independent. None of the correlations in the original matrix exceeded 0.85, thus multicollinearity was not observed, i.e., no two items measured the same aspect of the construct. Also, the determinant of the matrix was found to be greater than 0.0001 [94, 100], which supports the further use of the data set for EFA and principal component analysis reduction methods for this study. Three additional tests, i.e., Kairser-Meyer-Olkin, Bartlett, and Scree Plot, were conducted to affirm the viability of using the data set for EFA and Principal Component Analysis (PCA) analyses.

A Kaiser-Meyer-Olkin (KMO) test was also performed to validate that an appropriate number of sampling sizes were used in the study, e.g., sampling adequacy. A total of 304 students participated, however, only 227 of the participant data was used as incomplete surveys were discarded from the analysis. The KMO for this work was calculated to be 0.75 (shown in Table 3). Since KMO is equal to 0.750, this indicates that sample size is sufficient for factor analysis. Bartlett's Test for Sphericity was conducted to test the null hypothesis that the correlation matrix is an identity matrix. As shown in Table 3, sphericity significance

Table 3. KMO and Bartlett's test results for the questionnaire. The KMO value indicates that there was an appropriate sample size for the number of questions included within the instrument. The sphericity significance (<0.001) value indicates that there is an adequate number of correlations between the variables within the instrument to use the EFA method

Measure	Value
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.750
Bartlett's Test of Sphericity Approx. Chi-square	1360.871
Bartlett's Test of Sphericity df.	378
Bartlett's Test of Sphericity Sig.	<0.001

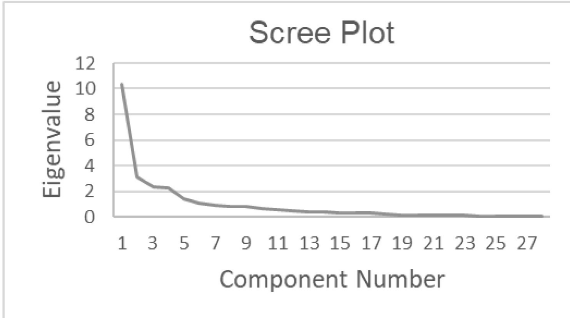

Fig. 2. Scree plot of the questionnaire questions and eigenvalues, which illustrate the presence of 6 factors.

was determined to be <0.001, which confirms that there are an adequate number of correlations between variables to conduct an exploratory factor analysis (EFA) [97].

To extract the number of factors underlying the data, two criteria were used: the point of inflection from the Scree Plot [101] and the number of eigenvalues greater than 1.0 [101, 102]. The Scree Plot containing the eigenvalues of the factors arranged in descending order of magnitude for the data for this study is provided in Fig.2 was used to ascertain the most meaningful factors of the structure [94]. Six factors were identified using this extract method, which are used to define the putative factor structure for the SPVEL instrument. Once the putative factor structure was identified, factor loadings were analyzed and reduced using the Principal Component Analysis (PCA) method [103].

6.4 Reduction Method – Principal Component Analysis (PCA)

A Principal Component Analysis (PCA) method was used to extract, define, and reduce the factor loadings, where the squared multiple correlations were used as prior communality estimates to extract the factors for this analysis. Rotated orthogonal matrix (Varimax with Kaiser Normalization [104]) and communalities were used to ascertain the loading of factors, where items with factor loading

Table 4. Percentage of total variance accounted for by each factor after the rotation process

Component factor	% of Variance
1	26.685
2	11.705
3	11.550
4	8.363
5	8.190
6	7.125

coefficients greater than |0.4| were considered significant for a specific factor, and those less than |0.40|, were removed. This process of analysis was repeated to optimize loading coefficient values and communality values, while minimizing loadings of variables that cross-loaded onto multiple factors. The final rotation converged in ten iterations. The questions that were removed from the questionnaire using this reduction and extraction method were Q2–Q7, Q24, and Q33. As mentioned previously, these were mostly appropriate for removal due to the limited number of choice options for participant responses, i.e., less than 5 response choices. Finally, Cronbach's Alpha was calculated for each factor to assess the reliability of the loading associated with the group. The final loading factor structure that comprised six factors along with the associated loading coefficients, Cronbach Alpha values are presented in the APPENDIX in Table 7. The rotated sums of the squared loadings are detailed in Table 4.

6.5 Instrument Factors

An Exploratory Factor Analysis (EFA) approach was used to decipher six primary factors including twenty-seven questions from the original set of thirty-five. Load factor one describes student perception of laboratory educational value towards enhancing students' skillset and reinforcement/enhancement of theoretical content taught in previous classes (TAM and IEO). Load factor two describes the interaction and communication between students and the instructor in the laboratory environment. The third load factor describes how students accepted/or not the laboratory environment, ease of use in from the TAM. The fourth load factor describes students' perception of the viability of virtual lab learning environment as a learning tool. The fifth load factor describes students' engineering role identities (EFI). The last and sixth load factor observed was students' perceptions of virtual learning environment ease of use and usefulness (TAM). As shown in the APPENDIX in Table 7, additional reliability tests were performed for each load factor, where Cronbach's alpha was determined for each of the load factors. Overall, the alpha scores for each factor were high ($\alpha \geq 0.67$), thereby confirming high reliability.

6.6 Load Factor One – Student Perception of Laboratory Educational Value

The first load factor has a total of nine variables loading into it. Cronbach's alpha for the variables associated with factor one is 0.944, which is extremely high. This factor refers to how students perceived the virtual laboratory experience in terms of value in enhancing their existing skills and/or technical knowledge. From Table 7, it can be deduced that Factor one contributed 26.685% of the total variance after rotation, which is the highest among the six factors.

6.7 Load Factor Two – Interaction and Communication Between Students and the Instructor

Four variables loaded into the second factor. This factor refers to communication between students and the instructor within the virtual labs experience. Factor 2 contributed to 11.705% of the total variance after rotation and its Cronbach's alpha was determined (for four variables) to be 0.857, which is very high.

6.8 Load Factor Three – Technology Acceptance (Ease of Use) and Engagement

The third factor has a total of five variables loading into it and refers to the attentiveness of the students in the virtual lab environment, as well as ease of use (TAM) of the virtual laboratory environment. It can be deduced from Table 7 that Factor 3 contributed to 11.550% of the total variance after rotation, where Cronbach's alpha after rotation was found to be 0.773. The high value of Cronbach's alpha suggests a high reliability for this load factor to predict students' opinions regarding how easy/or not it was to engage with the virtual laboratory environment remotely from home.

6.9 Load Factor Four – Students' Perception of the Viability of Virtual Lab Learning Environments as Learning Tools

The fourth factor has two variables loading into it and contributes to 8.363% of the total variance after rotation. It refers to a student's perceived understanding of virtual lab viability. The Cronbach's alpha for Factor 4 is 0.764. This load factor like the others has high reliability in the variable questionnaire questions within it.

6.10 Load Factor Five – The Fifth Load Factor Describes Students' Engineering Role Identities

The fifth factor has three variables loaded onto it that pertain to engineering role identity as defined by [74, 77]. Factor five contributed to 8.190% of the total variance after rotation. The Cronbach's alpha for load factor five is 0.674, which is average, i.e., between 0.5 and 0.7.

6.11 Load Factor Six – Students' Perceptions of the VL Environment Ease of Use and Usefulness (TAM)

Factor six has three variables loading within it and contributed to 7.125% of the total variance after rotation. It also has a Cronbach's alpha equal to 0.674, which is within an acceptable range (between 0.5 and 0.7). Factor six examines how students perceive the virtual learning environment in terms of ease of use and usefullness, which are elements from the TAM described in Section 3.1.

7. Discussion

In our previous work [12], we found that several questions in the conventional course evaluation instrument tended to be more instructor focused, rather than student focused. Hence feedback from students about the virtual lab session did not fully visualize students' points of view regarding the laboratory environment. Hence, one of the goals for this project was to generate more feedback from students regarding the virtual lab experience and utility.

Factor 1, derived from the EFA, relates to how students perceived the virtual laboratory experience in terms of value in enhancing their existing skills and/or technical knowledge. This factor also examines if the laboratory experience enhanced students' motivation to learn more about the laboratory topic outside of the classroom environment. In this way, the factor helps the researcher understand the tendency of the learner to allocate time towards gaining more knowledge, which is part of the I-O-E model. The I-E-O model also connects one's previous experiences and environment to output. In this case, the inputs to the model include previous experience with virtual lab environments and confidence in content mastery from previous classes taken in the subject of the laboratory. Inputs could also include social identity characteristics, which can be related to access to technology and novel learning platforms. When connected to student demographical information, this factor may be used to elucidate how students' motivation from the lab experiences are related to their background and prior experiences in a manner similar to [105], who used the I-E-O model to predict students' first choice in selection of engineering as a major to students' ethnicity, gender, and time of application. Factor 1 also illustrates how students perceive the lab to be of use in helping them prepare for their lab report, which is an extension of the TAM as it allows the instructor to *interpret* what is useful for the student, i.e., being able to successfully fulfil the lab report requirement based on the virtual lab experiences. In the original TAM, usefulness was based on predicting how the usefulness of the technology outweighed the effort put into learning how to use the technology. In our validated instrument, willingness to learn to use the technology for benefit is expressed in questions 18, 21, 27, and 35. Extending the Technology Acceptance Model (TAM) to include mechanisms pertaining to how users interpret usefulness has been the subject of scholars like [106], who related students' proclivity towards continuing to use an online engineering education game to how they perceived it to be useful in terms of preparation for an exam in the course or an engineering related job interview. Similarly, this work extends the TAM to understand students' perception of usefulness in terms of preparation for lab reports and development of skills to be used in a career. In a similar way, the TAM's definition of *ease of use* is extended in this work, via questions pertaining to the ability to follow the steps in the lab and the lab being a good learning experience.

Factor 2 refers to communication between the students and instructor in virtual lab environments. From previous work that used the traditional course evaluation tool, students were not able to communicate the level of engagement that they experienced with the course instructor, though this has been noted by others as a vital component of effective laboratory learning experiences [2, 12]. Hence, the addition of the questions that loaded onto Factor 2 for this instrument allows the researcher and practitioner to ascertain the effectiveness of their interaction with students using multiple schemas. This factor's ability to assess student-instructor engagement is important and aligns with the findings of [107] who asserted that it is critical that there should always be a pedagogic alignment between content knowledge and technology, which can lead to enhanced student-teacher interaction and active learning environments.

The third factor refers to the attentiveness of the students in the virtual lab environment, as well as ease of use (TAM) of the virtual laboratory environment, which was discussed in Section 3.1. This factor informs the instructor or instruction team/technologist, about aspects that influence students' ease of observing (visually) and hearing the lab as performed by the instructor. Cronbach's alpha of 0.773 suggests a high reliability of this load factor to predict students' opinions regarding how easy/or not it was to engage with the virtual laboratory environment remotely from home. In addition, this factor includes one question related to the I-E-O model, i.e., student's prior experience with using virtual labs. Inclusion of this question within load factor three suggests that there is a relationship between student's ease of using virtual lab technology and prior experiences with virtual labs. The high correlation between the variables in this group reinforces our previous work, where qualitative responses from students indicated that they lost concentration in virtual labs in instances where there were technology/internet challenges and visibility complications when observing steps in the experimental process due to camera vantage point. The Cronbach's alpha for Factor 3 (α = 0.77), compared to Factor 1 (α = 0.94) and Factor 2 (α = 0.86), is slightly lower due to there being fewer options in the instrument for the question about prior high school experience. This may have resulted in lower inter-relatedness between items and/or lower reliability from this multiple-choice question (with 3 choices of response) in comparison to the 5-point Likert scale used for the majority of the other questions in the instrument. The 11.55% of total variance for this factor is close to that for the second factor, which indicates that both factors have similar weights in terms of importance for these items for inclusion within the final instrument.

Factor four refers to a student's perceived understanding of a virtual lab's viability. From the feedback of the interview from previous work, it was perceived that while many students liked face-to-face lab sessions more, some were content with virtual lab sessions. To garner more student feedback regarding this matter while providing continual improvement on the virtual lab sessions, it is important to constantly ask for feedback regarding the viability of the virtual lab classes from the students' point of view. This aspect was not included in the set of questions within the conventional course evaluation instruments [12]. Factor four signifies this aspect and had the two variables closely representing the notion of whether a virtual lab is better than face-face and if students learn more or nearly the same in both types of labs.

The fifth factor has three variables that pertain to engineering role identity as defined by [74, 77]. Factor five has a Cronbach's alpha equal to 0.674. which is slightly lower compared to previous factors. This is mostly attributed to the lower relationship of the students' belief in their ability to use their skills as engineering students evidenced in them being able to understand engineering concepts in their courses. It is important to note, however that the extracted communality score for question 13 is 0.6, which is acceptable, i.e., above 0.4, for the reduction approach. This lower connection with the other variables indicates an opportunity for this instrument to garner evolving perceptions of student identities' affinity and the affection for their chosen field. It also sheds light on understanding their confidence in their ability to appreciate and use skills acquired in coursework and laboratories. This disconnect in personal confidence in engineering skillset and actual performance has been noted by [6]. Also, variability in student experiences, e.g., mentorship [108], parental support [109, 110], exposure to others in engineering like themselves [111, 112], may contribute to confidence, which are elements not included in this instrument, but found to relate to engineering role identity, engineering formation, and persistence in the engineering field [113], which undoubtedly influence the effectiveness of educational resources and learning tools. This question may also have lower inter-relatedness to the two other items because it may be interpreted differently by the students, or not provide enough context for students within the same department, but with different specific interests, e.g., thermal science, design, composites, etc. In addition, variability in confidence regarding one's abilities in a subject could be influenced by sentiments of imposter phenomenon [114, 115], which were not explored as a part of this study instrument.

Factor six describes how students perceived the virtual learning environment in terms of ease of use and usefulness, which are aligned with the TAM [60, 61, 116] . Table 7 shows that the question in this factor pertaining to usefulness of the lab to future work is ranked lower (0.624) than the other two questions in the grouping, related to VL's ease of use (0.760) and VL's can be good learning tool (0.718). This lower connection may be because of some students' inexperience with the engineering field from internships and co-ops, and other experiences with course work not directly appearing to relate to real-world engineering experiences. This could also be a reflection of the student's perceptions of the equipment and measurements used in the lab, which may not have been cutting edge from their vantage points. It is expected that this instrument will provide a unique opportunity to garner their evolving perceptions of the engineering profession and their personalized educational needs, which have been identified by the National Academy as a grand challenge in engineering [117] .

It is anticipated that the SPVEL assessment instrument can be used by researchers and instructors who facilitate and design engineering laboratories for 21st century engineering undergraduate and pre-college high-school science students. For example, the SPVEL instrument provides a meaningful way to assess how laboratory content relates to and affirms theoretical content taught in prior courses. This instrument also facilitates the exploration of communication and interaction between students and instructors, which is different from traditional assessment tools that focus on student assessment of instructor preparedness and not how students chose to actively participate in laboratory environments. The instrument also allows the instructor and researcher to examine how diverse types of laboratory environments, equipment, and tools are accepted (or not) as being useful for realistic professional skill development as interpreted by the student. Given the important relationship between students' association with their engineering role identity and persistence in the field, learning how laboratory environments affirm (or not) students positionality within the engineering field is vital. Understanding this relationship is crucial as educators contemplate evidence-based practices for updating and modernizing laboratory equipment, protocols, and subject matter in innovative novel ways.

8. Conclusion

An exploratory factor analysis was used to validate a questionnaire as an instrument for use in understanding the perceptions of students engaged in virtual laboratories. In this process, underlying factors within the questionnaire were identified and Cronbach alpha scores that were high to acceptable were achieved. Several questions were eliminated from the instrument due to low communality scores, i.e., lower than 0.4. The six factors gleaned from this study focus on students' perception of the lab's educational value; the effectiveness of the interaction and communication between the students and the instructor; the acceptance of the technology (TAM); viability of the virtual lab environment as an effective learning tool; and the influence of the lab on forming students' engineering role identities. Understanding how to design remote and virtual labs is a meaningful step towards developing personalized learning tools for engineering education. Also, this work provides an initial glimpse into how students align their practical demonstration labs with future career work. Understanding ways of preparing 21st engineering students for the 21st century engineering profession will require critical analysis of existing norms and ways of doing, fundamental engineering theory, teaching, and mechanisms/tools for assessment as the connection between coursework and practical application of theory. As the identity and expectations of the students and engineering curriculum evolves, so too will the profession and research in this field as they become more convergent in practice.

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Appendix

Table 5. List of Pre-lab questions administered to students prior to participation in the lab. The mean and standard deviation for each variable is provided along with the associated theoretical framework

Item	Category of Question and responses	Mean (M) ± STDEV	Theoretical Model
Prior virtual lab experience demographic information. Possible student choices: 0 Classes (0), 1 – 2 Classes (1), 3 or more classes (2)			
Q1	Have you ever engaged in a virtual lab in high school?	0.17 ± 0.49	
Q2	Have you every engaged in a virtual lab in college?	0.48 ± 0.58	**IEO Model**
Q3	How many in-person lab courses have you had since you started college?	1.74 ± 0.50	
Prior internship and undergraduate research experience. Possible student choices: None (0), 1 – 2 experiences (1), and 3+ experiences (2)			
Q4	Engineering internship	0.49 ± 0.63 (*58.1% no experience*)	**IEO Model**
Q5	Engineering research with engineering school	0.34 ± 0.59 (*53.9% no experience*)	
Prior experience - lab preparation classes other than MAE 14-650-431 (this course). Possible student choices: 0 – 1 hour (1), 2 – 3 hours (2), 4 – 5 hours (3), 6 or more hours (4), N/A (5)			
Q6	How many hours have you spent in the past preparing for hands-on labs.	1.76 ± 0.94 (50% 0–1hrs.)	**IEO Model**
Q7	How many hours have you spent writing lab reports (outside of class period) in college in the past (hands-on labs)?	3.04 ± 0.84 (74% 4+ hrs.)	
Perceptions of virtual labs (VLs) – Likert Scale of 1 to 5. Possible student choices: Strongly Agree (5), Somewhat Agree (4), Neither Agree nor Disagree (3), Somewhat Disagree (2), Strongly Disagree (1)			
Q8	I think VLs can be good learning tools.	3.23 ± 1.05	
Q9	I think virtual labs can replace hands-on-labs.	1.84 ± 0.97	
Q10	I think virtual labs are easier to do than hands-on-labs.	2.73 ± 1.00	**IEO**
Q11	I can learn as much virtual lab as I can from a hands-on-lab.	2.32 ± 1.08	
Q12	The skills from VLs will be useful to me in my future career.	3.23 ± 1.07	
Self-Identification with the Engineering Profession- Likert Scale of 1 to 5. Possible student choices: Strongly Agree (5), Somewhat Agree (4), Neither Agree nor Disagree (3), Somewhat Disagree (2), Strongly Disagree (1)			
Q13	I can understand concepts that I have studied in engineering.	4.34 ± 0.70	
Q14	Being an engineer is an important part of my self-image.	4.03 ± 0.99	**Engineering Role Identity**
Q15	My friends see me as an engineer.	4.14 ± 0.89	

Table 6. post-lab questions administered to students after they completed the virtual lab and submitted the final laboratory report, N = 227. *Likert Scale of 1 to 5 where 1 is Strongly Disagree, 3 is Neither Disagree or Agree, 5 is Strongly Agree*

Student Perceptions of VL Experience.			
Q16	The VL was easy to understand.	3.69 ± 1.05	
Q17	I could follow the steps in the lab.	3.70 ± 1.10	
Q18	The lab held my attention for the full duration of the time.	3.36 ± 1.23	
Q19	I was able to communicate with the TAs during the lab.	4.13 ± 0.97	**TAM +**
Q20	Class ran smoothly with no technical glitches.	3.48 ± 1.31	
Q21	This lab adequately prepared me to write my final report.	3.42 ± 1.15	
Q22	TAs effectively answered questions during the lab.	4.09 ± 0.95	
LabView virtual laboratory (VL) and in-person interactions and visual experiences.			
Q23	The operations performed in the lab were easy to follow.	3.79 + 1.09	
Q24	It was hard for me to see relevant steps/processes taking place in the lab.	3.11 ± 1.24	
Q25	I was able to ask questions in the virtual chat.	4.27 ± 0.90	**TAM +**
Q26	I was able to ask the TA questions orally during the lab.	4.27 ± 0.87	
Q27	I think I learned as much from this VL as I would have learned in a hands-on lab.	2.72 ± 1.41	
VL Connection with MAE prior coursework			
Q28	This VL helped me to understand concepts from my previous courses.	3.44 ± 1.19	
Q29	This VL affirmed concepts from my previous classes.	3.56 ± 1.14	
Q30	This VL helped me make the connections between previous course concepts.	3.57 ± 1.07	**IEO Model +**
Q31	The VL motivated me to want to seek more knowledge about this subject outside of class.	2.89 ± 1.31	
Q32	I was able to interpret the data from the lab using only resources provided in the class.	2.89 ± 1.31	
Usefulness of the virtual lab for future career			
Q33	I do not think that the real life of an engineer was reflected in this VL.	3.18 ± 1.15	**TAM +**
Q34	The virtual Lab was a good learning experience.	3.33 ± 1.19	
Q35	I think the skills I learned in this lab will be useful in my future career.	3.27 ± 1.23	
In this table, the "+" sign indicates that additional questions have been added to the model detailed to better understand student perceptions of the VL learning experience.			

Table 7. Rotated Component Matrix[a], which contains Cronbach's alpha that relates to the load factor. Minor cross-loadings not counted in the factor loading have been removed

<table>
<tr><th>Question</th><th>1
(α = 0.94)</th><th>2
(α = 0.86)</th><th>3
(α = 0.77)</th><th>4
(α = 0.76)</th><th>5
(α = 0.67)</th><th>6
(α= 0.67)</th></tr>
<tr><td>Q28: This VL helped me to understand concepts from my previous courses.</td><td>0.857</td><td colspan="5" rowspan="10">Load Factor 1 describes students' perception of the laboratory's value. This factor has nine variables loaded into it and illustrates the connection between usefulness of the lab in preparing course work materials and motivation to learn more for lifelong learning. This factor represents 26.685% of the total variance after rotation.</td></tr>
<tr><td>Q27: I think I learned as much from this VL as I would have learned in a hands-on lab.</td><td>0.855</td></tr>
<tr><td>Q29: This VL affirmed concepts from my previous classes.</td><td>0.833</td></tr>
<tr><td>Q34: The VL was a good learning experience.</td><td>0.796</td></tr>
<tr><td>Q30: This VL helped me make the connections between previous course concepts.</td><td>0.769</td></tr>
<tr><td>Q35: I think the skills I learned in this lab will be useful in my future career.</td><td>0.762</td></tr>
<tr><td>Q31: The VL motivated me to want me to seek more knowledge about this subject outside of class.</td><td>0.753</td></tr>
<tr><td>Q32: I was able to interpret the data from the lab using only resources provided in the class.</td><td>0.713</td></tr>
<tr><td>Q21: This lab adequately prepared me to write my final report.</td><td>0.707</td></tr>
<tr><td>Q18: The lab held my attention for the full duration of the time.</td><td>0.478</td></tr>
<tr><td>Q26: I was able to ask the TA questions orally during the lab.</td><td rowspan="9"></td><td>0.878</td><td colspan="4" rowspan="4">Load Factor 2 describes the interaction and communication between students and the instructor. This factor represents 11.705% of the total variance after rotation and has four variables loaded into it.</td></tr>
<tr><td>Q25: I was able to ask questions in the virtual chat.</td><td>0.842</td></tr>
<tr><td>Q19: I was able to communicate with the TAs during the lab.</td><td>0.737</td></tr>
<tr><td>Q22: TAs effectively answered questions during the lab.</td><td>0.696</td></tr>
<tr><td>Q17: I could follow the steps in the lab.</td><td rowspan="5"></td><td>0.734</td><td colspan="3" rowspan="5">Load Factor 3 represents 11.550% of the total variance after rotation and has 5 variables loaded into it. This factor describes the ease of use of the virtual lab system (TAM) and students' engagement.</td></tr>
<tr><td>Q16: The VL was easy to understand.</td><td>0.714</td></tr>
<tr><td>Q1: Have you engaged in a VL in high school?</td><td>–0.693</td></tr>
<tr><td>Q23: The operations performed in the lab were easy to follow.</td><td>0.595</td></tr>
<tr><td>Q20: Class ran smoothly with no technical glitches.</td><td>0.546</td></tr>
<tr><td>Q9: VLs can replace hands-on-labs.</td><td colspan="3" rowspan="2">Load Factor 4 describes the viability of the VL learning environment as a learning tool from the students' perspectives. This factor represents 8.363% of the total variance after rotation and has two factors loaded into it.</td><td>0.801</td><td colspan="2" rowspan="2"></td></tr>
<tr><td>Q11: I can learn as much in VLs as in hands-on-labs.</td><td>0.792</td></tr>
<tr><td>Q15: My friends see me as an engineer.</td><td colspan="4" rowspan="3">Load Factor 5 describes students' engineering role identities and contributes to 8.190% of the total variance after rotation, with three variables loaded into it.</td><td>0.890</td><td rowspan="3"></td></tr>
<tr><td>Q14: Being an engineer is an important part of my self-image.</td><td>0.882</td></tr>
<tr><td>Q13: I understand concepts that I have studied in engineering.</td><td>0.585</td></tr>
<tr><td>Q10: VLs are easier than hands-on-labs.</td><td colspan="5" rowspan="3">Load Factor 6 has three variables loaded into it and represents 7.125% of the total variance after rotation. This load factor represents students' perceptions of the VL's ease of use and usefulness (TAM).</td><td>0.760</td></tr>
<tr><td>Q8: VLs can be good learning tools.</td><td>0.718</td></tr>
<tr><td>Q12: The skills from VLs will be useful in my career.</td><td>0.624</td></tr>
<tr><td colspan="7">Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]</td></tr>
<tr><td colspan="7">a. Rotation converged in ten iterations.</td></tr>
</table>

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