Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #47963

Application of FLASH to Forecast Student Engagement in Online Engineering Courses

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WIP: Application of FLASH to Forecast Student Engagement in Online Engineering Courses

Abstract

Student engagement is a critical factor in online education, influencing both learning outcomes and retention rates. In online environments, students often face challenges such as lack of interactions, which can lead to disengagement and higher dropout rates. Engagement serves as a bridge between students and their learning materials, fostering active participation, deeper understanding, and sustained motivation. This is particularly crucial in engineering courses, where complex concepts require continuous interaction and application.

This research presents the application of the Forecasting Learning Achievement with Survival History (FLASH) methodology to predict student engagement and success in online engineering education, specifically focusing on thermodynamics and fluid mechanics courses. By utilizing Survival Analysis (SA) techniques, the study aims to identify key engagement factors and forecast academic outcomes, providing a framework for enhancing student retention. Survival Analysis (SA) serves as the core methodology of this research, involving the definition of key parameters such as the *survival* variable, which in this case refers to the likelihood of student persistence or success throughout the course. The *treatment* is the specific learning intervention applied. The *time interval* is defined by the duration of student participation in the course, during which engagement is monitored at multiple milestones.

In this research, the virtual environment (VE) is the selected treatment to enhance student engagement. While various treatments can be employed to boost engagement, such as interactive discussions, team-based projects, and traditional engineering assignments, this study specifically focuses on VEs. VEs offer immersive, interactive spaces that simulate real-world engineering challenges, providing students with opportunities to apply theoretical concepts in a dynamic and engaging context. The study aims to evaluate the effectiveness of this treatment compared to more traditional methods, with a particular focus on its impact on students' cognitive, psycho-motor, and affective skills.

The integration of Virtual Environments (VEs) serves as a comparative tool to traditional learning activities, aligning with the New Engineering Educators (NEE) division’s focus on innovative educational strategies and tools for faculty development, contributing to the long-term sustainability of engineering education.

Keywords:

Survival Analysis, Virtual Environments, Online Engineering Education, Student Engagement, FLASH Methodology

1. Introduction

Online education has transformed the landscape of engineering education, presenting both opportunities and challenges for engineering educators and students. Student engagement remains a pivotal factor influencing learning outcomes, retention rates, and overall student satisfaction. However, online environments pose unique challenges, such as limited interpersonal interactions and reduced opportunities for hands-on experiences, which can lead to disengagement and attrition. These challenges are particularly acute in engineering courses, where mastering complex concepts requires active participation and practical application.

This work introduces the application of the FLASH methodology, a novel approach that equips new engineering educators with tools to predict and enhance student engagement in online courses. By leveraging SA techniques, this study offers actionable insights to help educators identify critical engagement factors, forecast academic outcomes, and implement targeted interventions. This research specifically focuses on thermodynamics and fluid mechanics courses, showcasing how VEs can be used as a transformative educational tool. VEs simulate real-world engineering scenarios, providing students with immersive, interactive learning experiences that go beyond traditional methods.

The goal of this study is to share best practices and provide actionable recommendations for implementing VEs in online engineering education, thus contributing to the broader adoption of innovative teaching strategies within the field. It also provides a practical framework for faculty development, enabling new educators to foster student engagement, improve learning outcomes, and contribute to the long-term sustainability of engineering education.

1.1. Background

Virtual Environments (VEs) offer immersive, interactive learning spaces that simulate real-world engineering challenges. By enabling students to apply theoretical concepts dynamically, VEs can enhance cognitive, psycho-motor, and affective skills. Previous research has demonstrated the potential of VEs to improve engagement and learning outcomes, but their comparative effectiveness against traditional learning methods remains underexplored in online engineering education. This study addresses this gap by integrating VEs into the curriculum and assessing their impact on student engagement and retention [1,2].

In recent advancements, the concept of representation learning has gained significant attention for its ability to automatically learn useful features or representations from raw data, eliminating the need for extensive manual feature engineering [3]. This approach is particularly valuable in domains like machine learning, where the complexity of data can make traditional methods inefficient. In the context of education, representation learning can be applied to virtual labs to enhance student engagement and personalize learning experiences. By leveraging this approach, virtual lab systems can learn from student interactions, identify patterns in their behavior, and adapt the content or feedback to better suit individual learning needs. This enables a more dynamic and responsive learning environment, where the system can continuously refine its understanding of a student's grasp of the material and provide tailored support, much like an instructor guiding a student through difficult concepts.

Survival analysis (SA) predicts the probability of survival based on a medical treatment, often used to study patient outcomes, such as survival time after a disease diagnosis, relapse, recovery, or other medical events. This methodology identifies risk factors, informs treatment decisions, and provides valuable insights into patient prognoses [4−6]. Beyond medical research, SA has been applied in fields like sociology, engineering, economics, and education. In education, it is used to analyze events like dropout rates, time to graduation, or achieving milestones, offering actionable insights to improve educational outcomes [7−10].

The proposed work, Forecasting Learning Achievement with Survival History (FLASH), uses survival analysis to model the probability of students achieving milestones over time. This approach assesses engagement and predicts outcomes in educational contexts. The Kaplan-Meier survival function calculates the probability of surviving to a given time interval. In an academic setting, the survival parameters can represent student progression within a course or program, their engagement in particular activity within a semester or overall graduation in oppose to drop-out rate, all enabling the calculation of overall program completion probabilities.

In this study, VEs are proposed as a *treatment* to increase student success. VEs provide hands-on, scenario-based learning where students apply theoretical knowledge to simulated real-world projects. By bridging theoretical concepts with practical applications, VEs enhance learning, improve skill development, and offer an engaging educational experience [11, 12].

Integrated feedback mechanisms within VEs allow students to refine their strategies iteratively, creating a continuous improvement loop. Similar to varied treatments in medical SA, different VE approaches can be studied to determine their impact on student engagement and achievement.

1.2. Research Objectives

The primary objectives of this study are to:

a. Design and development of virtual environments for engineering core course as "*treatment*" to enhance engagement
b. Apply FLASH to forecast student success based on engagement data in VEs within individual engineering courses, such as Fluid Mechanics and Thermodynamics.

c. Identify critical factors contributing to engagement and disengagement in online engineering courses.
d. Evaluate the impact of VEs on cognitive, psycho-motor, and affective skills through project-based learning.
e. Develop strategies to improve teaching practices and retention rates in ERAU's engineering programs.

2. Approach

The research follows a three-phase approach:

Phase 1- Development and Implementation of VEs: In the first phase, VEs are developed and integrated into Fluid Mechanics courses to create immersive learning experiences. Preliminary engagement data were collected to establish baseline metrics and identify patterns in student interaction. This phase involved iterative refinement of the engagement measures, informed by direct student feedback and observational insights. The goal was to ensure the VEs were intuitive, engaging, and aligned with course objectives, enabling students to connect theoretical knowledge with practical applications effectively. This phase is now being followed up with developing new labs in Thermodynamics.

Phase 2- Comparative Analysis: The second phase focused on conducting a comparative study to evaluate the effectiveness of VE-enhanced activities relative to traditional teaching methods. Statistical analysis is employed to analyze key engagement milestones, such as engagement threshold, participation in VE activities and completion of VE-based projects. By correlating these milestones with academic success indicators, the study identifies critical moments where intervention can have the most significant impact. This phase highlights how VEs can provide richer learning experiences and foster higher levels of engagement compared to traditional methods.

Phase 3- Validation using FLASH: The final phase involves validating the findings from the earlier stages through comprehensive data analysis using FLASH model. This phase aims to share actionable insights and evidence-based conclusions regarding the effectiveness of virtual labs in enhancing student engagement and academic performance. By leveraging the FLASH model, we can analyze key variables, identify trends, and ensure the robustness of the results, ultimately providing a solid foundation for future applications and improvements in virtual lab implementations. Additionally, the findings will be instrumental in refining future virtual lab developments in Thermodynamics, ensuring that the labs are optimized to meet learning objectives and further enhance student outcomes. The three-phase approach is shown in **Figure 1**.

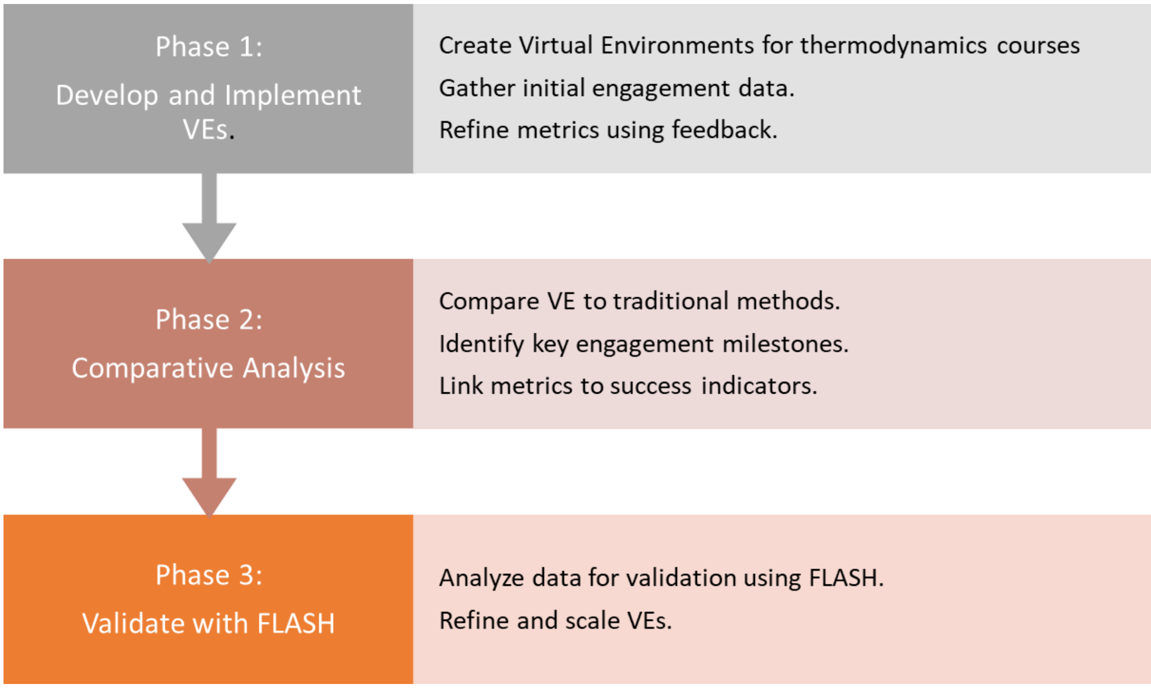

Figure 1: Three-Phase approach

3. Analysis & Results

This section outlines the systematic three-phase approach employed to develop, implement, and evaluate virtual lab activities, leveraging data-driven methodologies to assess their impact on student engagement and learning outcomes.

3.1. Phase 1: Development and Implementation of VEs

The selection of appropriate instructional tools is a critical component of effective education. Recent research indicates that the pedagogical use of virtual environments (VEs) can significantly enhance learner outcomes by fostering a greater sense of achievement and improving learning performance [11, 12]. These findings suggest that VEs serve as valuable tools for promoting student success.

As mentioned before, for engineering students in an online, asynchronous learning modality, VEs are particularly impactful. They provide a more immersive and interactive learning experience compared to traditional lecture-based courses. VEs enable students not only to observe experimental results and simulations but also to interact with the environment, simulating hands-on experiences.

In designing the virtual labs for Fluid Mechanics, we primarily focused on some complex concepts, aiming to provide students with interactive, visual, and dynamic tools that help improve student comprehension. The selection of topics such as viscosity, pressure distribution, and conservation laws (including mass, energy), and linear momentum for virtual lab design is rooted in their foundational importance in fluid mechanics and thermodynamics, as well as the challenges students often face in understanding these concepts. These topics are critical for building a comprehensive understanding of fluid behavior and the principles governing thermodynamic systems, making them essential in engineering education [13]. Here's a deeper look into why these topics were chosen:

3.1.1. Viscosity Lab

Viscosity is a measure of a fluid's resistance to flow and deformation. Understanding viscosity is crucial because it influences the design and performance of various engineering systems, such as pumps, pipes, and automotive engines. Students often struggle to visualize and quantify the effects of viscosity, as it involves both macroscopic and microscopic properties of fluids. A virtual lab can help simulate these effects under various conditions, making the concept more tangible and intuitive. The relationship between the shear stress and the velocity gradient in a fluid flow is given by *Newton's Law of Viscosity,* Eq. (1):

$$\tau = \mu \left(\frac{du}{dy}\right) \tag{1}$$

Where τ is the shear stress, μ is the dynamic viscosity (a fluid property), and $\frac{du}{dy}$ is the velocity gradient perpendicular to the flow direction [13].

3.1.2. Pressure Distribution Lab

Pressure distribution within a fluid plays a key role in understanding fluid behavior in various systems, such as pipes, ducts, and open-channel flows. Students frequently find pressure distribution concepts challenging because it involves understanding the spatial variation of pressure in static and dynamic fluid systems. Virtual labs enable students to explore how pressure changes with depth, velocity, and boundary conditions, providing an immersive experience to reinforce these abstract concepts.

In a static fluid, pressure variation with depth is governed by *Pascal's Law* and can be expressed as Eq (2):

$$\frac{d\mathrm{P}}{dz} = -\rho \mathrm{g} \tag{2}$$

Where is P the pressure, ρ is the fluid density, g is the gravitational acceleration, and z is the depth (height in the vertical direction). This is the first step to understand the basics of fluids dynamics where the pressure distribution can be influenced by fluid velocity and *Bernoulli's* equation, Eq. (3):

$$\mathrm{P} + \frac{1}{2}\rho \mathrm{V}^2 + \rho \mathrm{g} z = C \tag{3}$$

Where V is the fluid velocity and *C* is a constant [13].

3.1.3. Control Volume Analysis Lab

The conservation laws, which include the conservation of mass and energy, as well as linear momentum, are fundamental to fluid dynamics and thermodynamics. Students often struggle with the conceptual and mathematical formulations of these laws, especially when applied to complex systems like flow through pipes or engines. Virtual labs offer opportunities to visualize and experiment with these principles, facilitating a deeper understanding of the governing equations including *Continuity* and *Linear Momentum* Equations, respectively Eqs.4 and 5:

$$\frac{d}{dt}\int \rho d\mathcal{V} = 0 \tag{4}$$

$$\frac{d}{dt}\int \rho \mathbf{V} d\mathcal{V} \ + \oint \rho \mathbf{V}(\mathbf{V}.\hat{n}) dA = \sum \mathbf{F}_{ext} \tag{5}$$

Where the first term on left-hand side of the Eq (5) is the rate of change of momentum within the control volume and the second term is the net flux of linear momentum through the control surface. The right-hand side represents the sum of external forces (such as pressure forces, viscous forces, and body forces like gravity) acting on the control volume [13]. The governing equations presented in these topics are essential for providing a mathematical framework that supports student learning, allowing for more meaningful exploration of how real-world systems behave under different conditions.

To support these goals, three virtual environments have been developed and implemented in Fluid Mechanics course offered in ERAU-Worldwide. *Virtual Rotary Viscometer Lab:* This VE allows students to measure the viscosity of fluids using a virtual rotary viscometer. *Atmospheric Pressure Lab:* Students can explore the relationship between pressure and altitude across different atmospheric layers. *Water Jetpack Simulation Lab:* This lab demonstrates the application of conservation of mass, linear momentum, and *Bernoulli's* equation to analyze the steady-state operation of a water jetpack device [14]. Each virtual lab includes features that enable students to control experimental parameters, collect data, and interpret results. By offering these capabilities, the labs not only replicate key aspects of physical experiments but also enhance the depth of student engagement and learning. The viscosity and momentum virtual environments are shown in **Figure 2**.

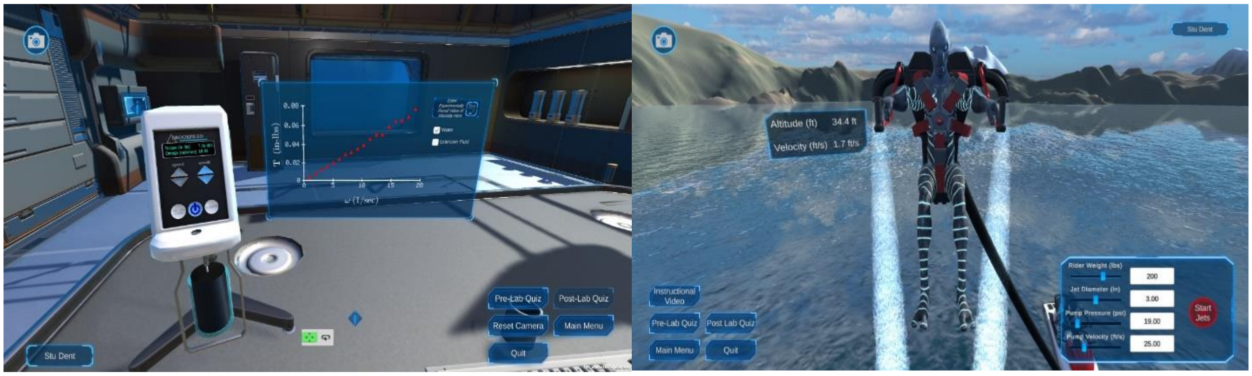

Figure 2- Designed VEs in Fluid mechanics: left: Viscosity Laboratory Image; right: Momentum Laboratory Image [14]

We also started developing virtual environments for Thermodynamics. This new VE focuses on the analysis of the components of the First Law of Thermodynamics. The lab is designed to provide students with an interactive platform to explore and apply core thermodynamic principles in a controlled, simulated environment.

In this lab, students will analyze the relationship between energy input and output in a thermodynamic system, specifically through the work done by a rotating paddle wheel. The VE allows students to adjust parameters and observe how changes affect the energy transformation process. Below are the key components of the lab:

- **Power Source**: The virtual system simulates a power source that generates energy by rotating a paddle wheel at a set RPM (revolutions per minute) under a given torque. This allows students to see how mechanical energy is converted into work over time.
- **Thermocouple**: Temperature measurement is facilitated by a thermocouple that records temperature at both the initial and final states, providing real-time data on thermal changes during the energy transformation process.
- **Simulink Sequence**: As shown in **Figure 3**, the entire virtual lab sequence is visually represented in Simulink, a prototype of exploring the basic functionality and interaction schemes of the lab. With that, we make sure to provide students with a step-by-step guide to understanding the progression of energy transfer and helping them calculate work, heat, and internal energy changes in accordance with the First Law of Thermodynamics.

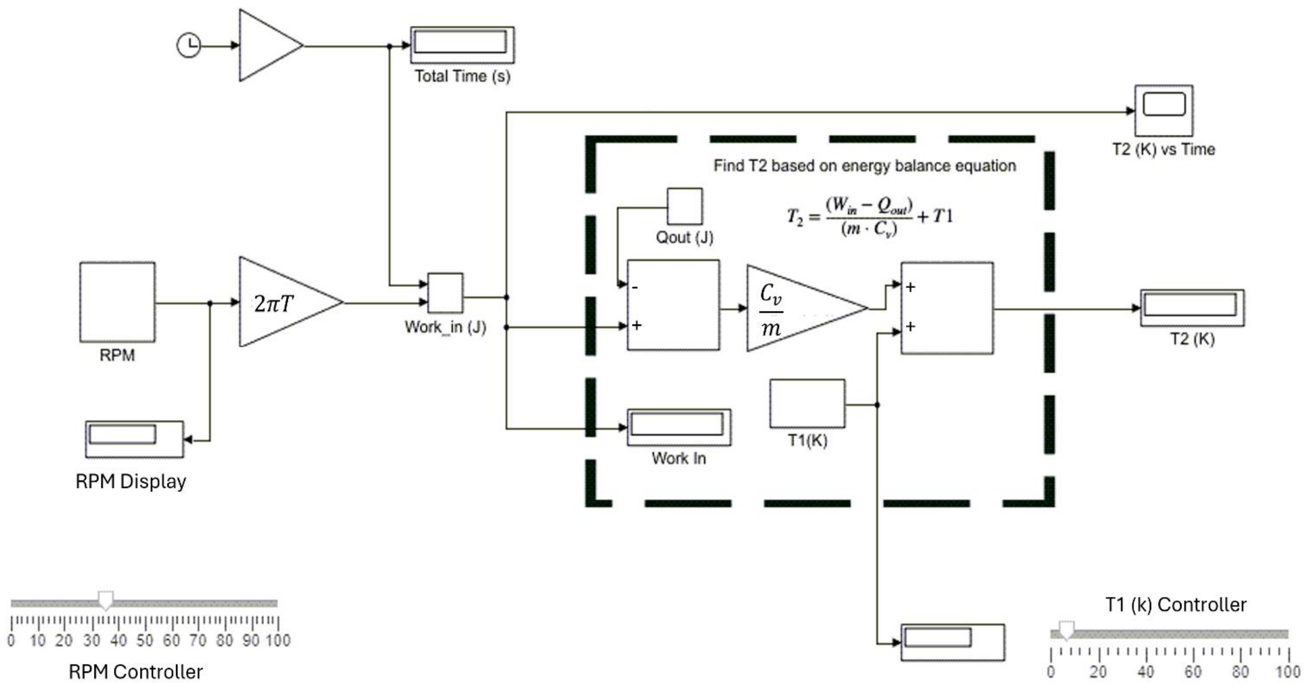

Figure 3: Thermodynamics virtual lab sequence, visually represented in Simulink

3.2. Phase 2: Comparative Analysis

To quantitatively measure student engagement in virtual labs, we propose a weighted scoring system that integrates multiple key indicators of student activity. The goal of this system is to provide a comprehensive and normalized engagement score by evaluating distinct aspects of student interaction with the virtual lab environment.

3.2.1. Indicators of Engagement

The following indicators are used to assess engagement:

1. *Number of logins (L)*: The total number of times a student accesses the lab environment.
2. *Time spent on instructions and learning materials (I)*: The duration students spend reading or watching the instructional material associated with the lab.
3. *Time in lab activities (T)*: The total time spent completing various levels and activities within the lab.
4. Pre-lab quiz data:
    - *Number of attempts (PNA)*: The total attempts made on the pre-lab quiz.

- *Quiz score (PNS)*: The score achieved on the pre-lab quiz.
- *Time spent (PNT)*: The total time spent on the pre-lab quiz.

5. Post-lab quiz data:
    - *Number of attempts (PSA)*: The total attempts made on the post-lab quiz.
    - *Quiz score (PSS)*: The score achieved on the post-lab quiz.
    - *Time spent (PST)*: The total time spent on the post-lab quiz.
6. *Total grade (G)*: The final grade received for the lab.

3.2.2. Weight Assignment and Calculation

To balance the influence of these indicators, we assign weights based on their relative importance in determining engagement. **Table 1** summarizes the weights assigned to each engagement indicator in the proposed scoring system. The relative importance of each engagement indicator was assigned based on a combination of prior research findings on student engagement, expert judgment, and preliminary analysis of student interaction data from previous course offerings. Specifically, preliminary engagement data were collected from prior implementations of virtual labs in Fluid Mechanics courses, allowing us to observe trends in student behavior. This data helped refine the weight distribution by identifying which indicators had stronger correlations with student participation and success.

Table 1: Scoring system: the weights assigned to each engagement indicator

Engagement Indicator	Symbol	Weight	Description
Number of logins	L	0.1	The total number of times a student accessed the virtual lab environment.
Time spent on instructions	I	0.1	The total time spent reading or watching the lab instructions.
Time in lab activities	T	0.3	The total time spent completing various levels and activities in the lab.
Pre-lab quiz attempts	PNA	0.05	The number of attempts made on the pre-lab quiz.
Pre-lab quiz score	PNS	0.1	The score achieved on the pre-lab quiz.
Pre-lab quiz time spent	PNT	0.1	The time spent completing the pre-lab quiz.
Post-lab quiz attempts	PSA	0.05	The number of attempts made on the post-lab quiz.
Post-lab quiz score	PSS	0.1	The score achieved on the post-lab quiz.
Post-lab quiz time spent	PST	0.1	The time spent completing the post-lab quiz.
Engagement Score	E	**1**	**The total engagement score received for the lab.**

The weights sum up to 1.00, ensuring a balanced and comprehensive scoring system for measuring student engagement. This distribution reflects the relative importance of each indicator in contributing to the overall engagement score. While time spent in lab activities (T) was given the highest weight (0.3) due to its direct relationship with active engagement, other indicators such as pre- and post-lab quiz scores and time spent on instructions were weighted based on their observed contribution to overall engagement.

The engagement score (E) is calculated as a weighted sum of the normalized values of these indicators, Eq. (6):

$$E = 0.1L + 0.1I + 0.3T + 0.05PNA + 0.1PNS + 0.1PNT + 0.05PSA + 0.1PSS + 0.1PST \tag{6}$$

3.2.3. Normalization of Data

Since the raw values for each indicator can vary significantly, normalization is essential to ensure fair comparisons and proper weight distribution. Each indicator is normalized using the maximum observed value in the dataset, Eq. (7):

$$Normalized\ Value = \frac{Raw\ Value}{Maximum\ Observed\ Value} \tag{7}$$

Indicators such as quiz scores and grades, typically expressed as percentages, do not require additional normalization.

The proposed weighted scoring system offers a framework for evaluating student engagement in virtual labs. By integrating multiple indicators and normalizing the data, this system ensures a balanced and holistic assessment that can inform both instructional design and educational research.

3.3. Validate the Data Using the FLASH Model

In this phase, we utilize comprehensive data analysis techniques, including the application of the FLASH model and survival analysis, to validate the efficacy of the VEs. To assess participation patterns and to understand the overall student engagement, we started by visualizing the distribution of engagement scores for students in three virtual labs offered in Fluid Mechanics. We used histograms, which is an effective tool for this purpose, as it allows for clear representation of the frequency of different engagement score ranges across students. In this section, we will also discuss how we apply survival analysis using FLASH model and how to interpret the results for instructional improvements.

The primary objective of visualizing engagement scores through histograms is to:

- Understand the distribution of engagement across all students in each virtual lab.
- Identify patterns or trends, such as whether a majority of students are highly engaged or if there is a significant portion of students with low engagement.
- Compare engagement across the three virtual labs to detect any differences in student participation, which may inform future course design decisions.

To define an engagement score that serves as the threshold between disengaged and engaged students, a data-driven approach is utilized. The process begins with calculating the mean and standard deviation of the engagement scores across the dataset to understand the central tendency and variability. A histogram is then plotted to visualize the distribution of engagement scores, helping identify natural groupings or cutoffs within the data. A common approach is to consider students with engagement scores below one standard deviation from the mean as disengaged, while those above this threshold are classified as engaged. This method ensures that the threshold reflects the overall behavior of the cohort, taking into account both the average level of engagement and its spread. Alternatively, subject matter expertise and qualitative insights, such as expectations for participation and performance in virtual labs, can also refine the cutoff to align with educational goals and practical observations.

The histograms reflecting engagement scores across the three virtual labs—Viscosity Lab, Pressure Lab, and Momentum Lab is shown in **Figure 4**. The histograms highlight critical patterns and provide insights into the factors influencing student engagement. The clustering of scores within specific ranges suggests variability in how students interact with and benefit from each lab. To determine a threshold between disengaged and engaged students, the histogram can be analyzed to identify a natural cutoff where engagement scores begin to cluster into higher ranges.

Table 2 summarizes key statistical metrics—mean, standard deviation, and lower quartile—for the engagement scores of the three VLs. The mean represents the average engagement score, providing a central measure of student participation. The standard deviation indicates the variability of engagement scores, with higher values reflecting greater dispersion among students. The lower quartile represents the score below which 25% of the students fall, offering insights into the least-engaged segment of the class. The Viscosity Lab shows the highest mean engagement score (0.26) and the largest variability (standard deviation of 0.1403). The Pressure Lab has a slightly lower mean engagement score (0.23) and a smaller standard deviation (0.1005), indicating more consistent engagement. The Momentum Lab, conducted later in the semester, exhibits the lowest variability (standard deviation of 0.0643) and a lower quartile similar to the others (0.181). These metrics provide valuable insights into student engagement trends and highlight differences in participation across the labs.

Table 2: Statistical Summary of Engagement Scores Across Three Virtual Labs: Mean, Standard Deviation, and Lower Quartile

Lab	Mean	Standard Deviation	Lower Quartile
Viscosity Lab	0.26	0.1403	0.183
Pressure Lab	0.23	0.1005	0.163
Momentum Lab	0.23	0.0643	0.181

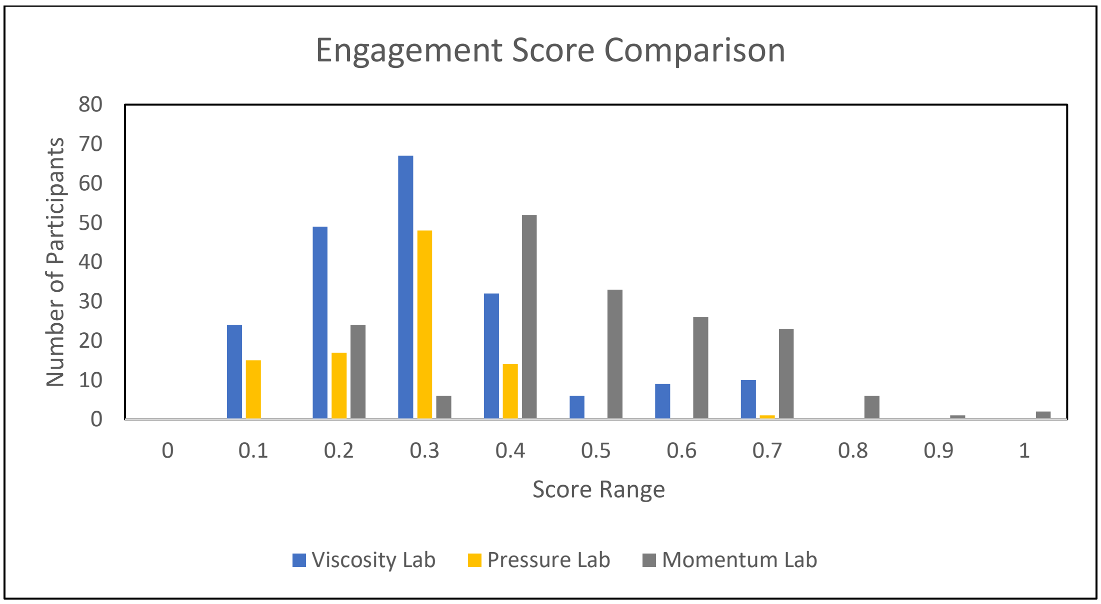

Figure 4: The histograms reflecting engagement scores across the three virtual labs—Viscosity Lab, Pressure Lab, and Momentum Lab

3.3.1. Engagement Score Comparison

The engagement score comparison reveals distinct patterns across the three virtual labs: Viscosity Lab, Pressure Lab, and Momentum Lab. The Viscosity Lab shows the highest concentration of participants with engagement scores in the range of 0.2–0.3, peaking at approximately 70 participants, but engagement drops sharply beyond 0.4, with minimal participation above 0.7. Similarly, the Pressure Lab also demonstrates a clustering of participants in the 0.2–0.3 range, though with a lower peak around 40 participants, and an even more constrained distribution with negligible representation beyond 0.5. In contrast, the Momentum Lab displays a broader and more evenly distributed range of engagement scores. A significant number of participants scored between 0.4–0.5, and engagement extended up to 0.7, suggesting higher overall participation and sustained interest compared to the other two labs. These observations indicate that while the Viscosity and Pressure Labs effectively promoted moderate engagement, the Momentum Lab outperformed them in fostering deeper and more sustained student engagement. In summary:

- Lower Engagement Clusters: Most students fall into the engagement score range of 0.2–0.4 for the Viscosity and Pressure Labs, with a peak around 0.3.
- Momentum Lab: The Momentum Lab shows a shift towards higher engagement scores, with a notable number of students in the 0.4–0.7 range.
- Score Concentration: Few students have engagement scores above 0.7, and scores beyond 0.8 are rare across all labs.

A reasonable threshold for defining disengaged versus engaged students could be set at **0.25**. This value marks the upper boundary of the most common engagement ranges for the Viscosity and Pressure Labs, while also serving as a point where the Momentum Lab transitions to higher engagement levels. Students with scores below 0.25 are considered disengaged, while those at or above 0.25 demonstrate acceptable engagement levels. This threshold reflects the patterns observed in the histogram and aligns with the shift toward higher engagement in later labs, potentially indicating improved student proficiency and participation as the semester progresses.

3.3.2. Possible Influencing Factors

Several factors may have contributed to the observed engagement trends. Notably, the timing of the labs within the semester plays a significant role. The Viscosity and Pressure Labs, conducted during the first four weeks of the semester, coincide with the early learning phase when students may still be acclimating to the virtual lab environment and mastering fundamental concepts. This timing might partially explain the concentration of scores in the 0.2–0.3 range, as students are still developing their proficiency and confidence in navigating the lab activities. Conversely, the Momentum Lab, conducted later in the semester, reflects higher engagement scores, with a significant cluster around 0.5. By this point, students are likely more proficient in the virtual lab environment, better equipped to handle complex tasks, and more comfortable applying their knowledge, which enhances their overall engagement.

Other factors, such as the complexity of the lab content, the level of interactivity, or the availability of support resources, may also have contributed. The Viscosity and Pressure Labs may lack sufficient interactive elements or scaffolding to sustain engagement, while the Momentum Lab's broader distribution of scores suggests its content and design may have been more effective at fostering sustained and meaningful participation.

3.3.3. FLASH Model Analysis

To assess student engagement and disengagement over the course of the semester, we employed Flash model which is based on survival analysis. Survival analysis is a statistical method used to analyze time-to-event data, where the event of interest, in this case, disengagement, is treated as a failure or "death." The FLASH model was used to model engagement and disengagement patterns, providing a framework for understanding student behaviors in an online learning environment. The first step in FLASH is to define the survival parameters. In this study:

- *Survival (Engagement):* Survival was defined as a student's continued engagement, determined by their interaction metrics and adherence to course activities.
- *Event (Disengagement):* Disengagement was defined as the point where a student's engagement score fell below a predefined threshold of 0.25, signaling a significant drop in participation.

The engagement threshold was set at 0.25 based on the analysis in the previous section and observed behavioral patterns in online learning environments. Students scoring below this threshold were considered disengaged, as their activity levels were insufficient to meet course requirements or learning outcomes.

The study cohort included 197 students enrolled in the course over a 9-week duration. Data were collected on weekly engagement scores, calculated as a composite of participation in virtual labs, time spent on different levels, prelab and post lab quizzes scores, etc. For reviewing the full list, refer to **Table 1**. Other metrics associated with engagement, such as interactions with discussion boards, course materials, and assignment grades, were also available. However, this study aimed to isolate the specific impact of virtual labs. Therefore, we focused exclusively on parameters directly influenced by virtual lab activities. Disengagement events were recorded at Weeks 2, and 8.

Survival analysis was conducted using the Kaplan-Meier estimator to calculate survival probabilities at each event time. The Kaplan-Meier method is well-suited for handling censored data, allowing for students who remained engaged throughout the semester or who withdrew from the course for reasons unrelated to disengagement to be accounted for in the analysis.

1. *Kaplan-Meier Estimation**:*** The Kaplan-Meier estimator, Eq. (8), was used to calculate survival probabilities S(t) at each time point [15−18]:

$$S(t) = \prod_{t_i < t} \left(1 - \frac{d_i}{n_i}\right) \tag{8}$$

Where d_i is the number of disengagements at time t_i, and n_i is the number of students at risk at time t_i.

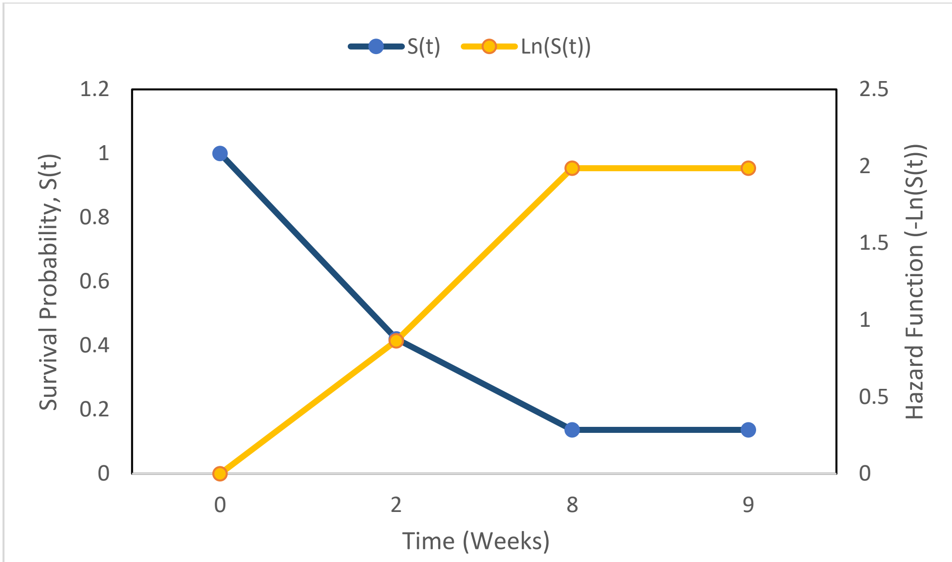

Figure 5: Survival analysis for the students' engagement using Flash model

The survival curve was plotted as demonstrated in **Figure 5**, showing the probability of students remaining engaged over time. Horizontal plateaus represented periods of stability, while drops corresponded to disengagement events. The hazard function shows the points of disengagement. Students are grouped based on their engagement trajectories, identifying clusters of high, moderate, and low-engagement learners. The model provides hazard ratios for disengagement events, quantifying the risk associated with specific factors such as lack of virtual lab participation, low initial engagement, and delayed assignment submissions.

The FLASH model's flexibility allowed for a nuanced understanding of engagement dynamics, highlighting key intervention points to improve retention.

To evaluate the impact of virtual labs on engagement, we compared students' submission grades for a specific momentum-focused virtual lab activity. This activity had previously been delivered as a discussion-based assignment in earlier iterations of the course. By transitioning the discussion to a hands-on virtual lab, we aimed to assess whether the interactive and experiential nature of the virtual lab enhanced student engagement and performance. The comparison as shown in **Figure 6**, focused on grade distributions, providing a comprehensive evaluation of the effectiveness of the virtual lab in fostering deeper understanding and participation.

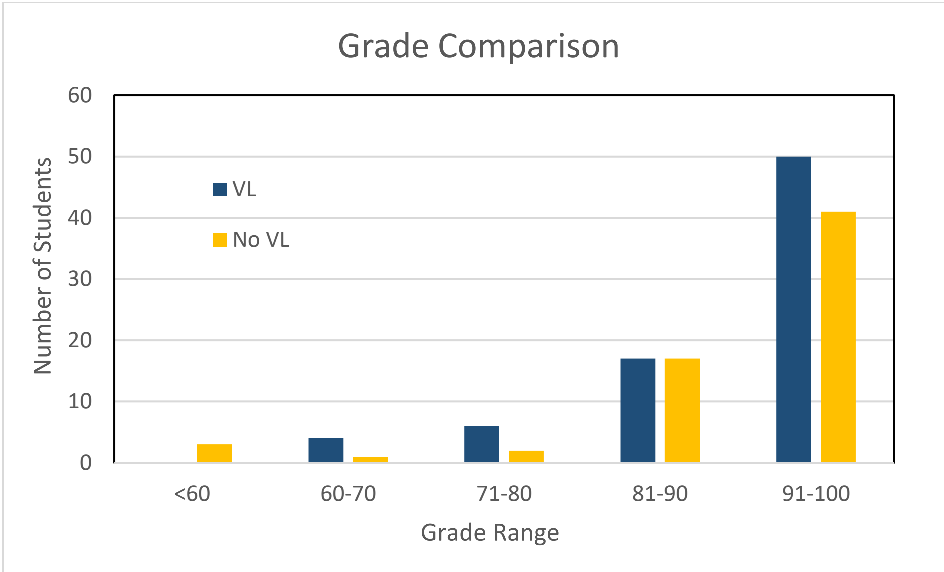

Figure 6: comprehensive evaluation of the effectiveness of the virtual lab

The grade comparison between students who participated in the VL and those who did not (No VL) highlights the significant impact of virtual labs on student performance. Most students in the VL group achieved grades in the 91–100 range, with nearly 50 students performing at this level, compared to a smaller number in the No VL group. This indicates that the hands-on, interactive nature of virtual labs may enhance students' understanding and their ability to achieve high performance. While the number of students scoring in the 81–90 range is comparable between the two groups, the VL group consistently shows stronger performance overall, particularly at the highest-grade range.

At the lower grade levels (<60 to 71–80), the No VL group has slightly more students, suggesting that virtual labs may provide additional support for struggling learners, helping them avoid low scores. Overall, the results demonstrate that the integration of virtual labs fosters deeper engagement and better academic outcomes, especially for students aiming for top grades. These findings support the hypothesis that virtual labs offer a more effective and engaging learning experience compared to traditional discussion-based assignments. Further investigation, including qualitative feedback and engagement metrics, could provide additional insights into the benefits of virtual labs.

The use of survival analysis, augmented by the FLASH model, provided actionable insights into student engagement patterns in an online learning environment. The analysis underscored the importance of early intervention, particularly for students at risk of disengagement. Moreover, the significant treatment effect of virtual labs suggests that interactive, hands-on learning experiences are critical for sustaining engagement.

Future work will explore integrating predictive analytics into the learning management system to proactively identify and support at-risk students, leveraging the FLASH model to enhance educational outcomes.

To enhance engagement beyond visual stimulation, we propose integrating real-time adaptive feedback mechanisms within the VEs. By leveraging FLASH's predictive capabilities, engagement patterns can be continuously analyzed to identify students at risk of disengagement. Based on this data, automated and personalized feedback can be deployed at critical learning milestones, ensuring students receive timely support. Future work will focus on designing and testing these mechanisms to ensure that feedback is not only timely but also contextually meaningful for students.

3.3.4. Adjustments Based on Findings

The visual patterns suggest targeted recommendations for improving engagement in future virtual lab iterations including thermodynamics labs. For conceptual labs such as Pressure Lab, introducing more interactive and gamified elements could encourage students to spend more time and remain engaged. Given their early-semester placement, these labs should include additional scaffolding to support students who are still building their foundational skills. Clear instructions, timely support, and feedback mechanisms can further address early barriers to engagement.

For the Momentum Lab, which demonstrated higher engagement, these findings reinforce the importance of maintaining an interactive and well-structured approach. Enhancing adaptive content delivery and offering challenging tasks that align with student proficiency at this stage in the semester can further optimize engagement.

By considering both the timing within the semester and the nature of the labs, future virtual labs can be strategically designed to maximize learning outcomes and foster meaningful participation throughout the course. Adjustments are made to the thermodynamics VEs based on the insights gained, ensuring their effectiveness and scalability.

4. Conclusion

This study highlights the transformative potential of Virtual Environments (VEs) in addressing the challenges of student engagement in online engineering education. By integrating immersive VEs into courses such as fluid mechanics and thermodynamics, we observed significant improvements in student participation, conceptual understanding, and overall academic performance. Employing FLASH model, coupled with SA techniques, allowed for a robust evaluation of engagement trends, providing actionable insights for designing effective educational interventions.

The results from this study underscore several key findings:

1. **Engagement Thresholds and Patterns:** The Kaplan-Meier survival curves demonstrated a critical engagement threshold of 0.25, with students scoring below this value significantly more likely to disengage. For example, the early-semester Viscosity and Pressure Labs had most students clustered within engagement scores of 0.2–0.3, whereas the later Momentum Lab showed broader and higher engagement scores, with a peak range of 0.4–0.7. This progression highlights the importance of timing and the growing familiarity students develop with VE tools over the semester.
2. **Impact of Virtual Labs on Performance:** The grade distribution comparison revealed that students engaging in VE-based labs outperformed those in traditional discussion-based assignments. For instance, nearly 50 students in the VE group achieved grades in the 91–100 range, compared to fewer in the non-VE group. This indicates that the hands-on, interactive nature of VEs fosters a deeper comprehension of core engineering principles.
3. **Variability in Lab Effectiveness:** Among the fluid mechanics VEs, the Momentum Lab demonstrated the highest engagement and performance, likely due to its interactive and conceptually rich design. In contrast, the early Viscosity and Pressure Labs, while effective in introducing basic principles, showed limited sustained engagement. This suggests that early labs might benefit from additional interactive elements, clearer scaffolding, and gamified features to bridge the initial learning curve.

The thermodynamics VE under development shows great promise, particularly in its ability to dynamically visualize the relationships defined by the First Law of Thermodynamics. By allowing students to manipulate variables such as power input, temperature, and system torque, this lab engages students in active learning and critical thinking. The inclusion of real-time feedback and data visualization further enhances the learning experience, enabling iterative exploration and reinforcing theoretical knowledge through practical application.

Building on these findings, several avenues for future exploration are proposed:

1. **Scalable Lab Designs:** Develop a suite of thermodynamics VEs, including labs on entropy analysis, heat transfer, and phase change phenomena. These labs should incorporate varying levels of complexity to accommodate both foundational learning and advanced applications.
2. **Enhanced Interactivity:** Introduce gamification, adaptive difficulty levels, and scenario-based problem-solving to make early labs more engaging. For example, incorporating virtual troubleshooting tasks or competitive elements could motivate students to deepen their participation.
3. **Real-time Intervention Systems:** Use the FLASH model to create predictive analytics tools within the LMS. By identifying at-risk students early, instructors can implement

tailored interventions, such as targeted feedback, personalized study plans, or collaborative learning opportunities. To fully realize the potential of FLASH and VEs in online engineering education, future work will focus on enhancing feedback mechanisms. Specifically, we will investigate the integration of automated feedback systems within VEs, leveraging AI-powered tools and intelligent tutoring systems to provide real-time, personalized feedback based on student performance.

4. **Cross-Course Integration:** Evaluate the effectiveness of VEs in other engineering courses, such as materials science or aerodynamics, to determine their scalability and interdisciplinary potential.
5. **Comprehensive Evaluation Metrics:** Expand assessment criteria to include cognitive, psychomotor, and affective domains, ensuring a holistic understanding of VE impacts on student learning. Collecting qualitative feedback alongside quantitative data can offer deeper insights into student experiences.
6. **Representational Learning Enhancements:** Research has shown that representational learning, which leverages visual and interactive models, is critical for understanding abstract and complex engineering concepts [19,20]. By incorporating advanced visualizations and dynamic simulations into VEs, students can better grasp ideas like energy transformations and fluid dynamics, which are otherwise challenging to visualize in traditional learning environments. Enhancing representational learning in VEs not only improves knowledge retention but also equips students with the skills to apply theoretical principles to real-world scenarios, a key objective in engineering education. Future work should explore the most effective types of visual and interactive representations for improving cognitive engagement and performance.
7. **Longitudinal Studies:** Conduct extended research to assess the long-term impact of VEs on retention rates, professional preparedness, and career outcomes. These studies could guide continuous improvement in VE design and pedagogical strategies.

This study establishes a compelling case for the integration of VEs as an indispensable tool in online engineering education. By fostering active learning and bridging the gap between theoretical concepts and practical applications, VEs have the potential to redefine the online engineering learning experience. Future studies should continue to refine these tools, ensuring they are accessible, effective, and scalable for diverse educational contexts.

Acknowledgment

This work was supported by ERAU Faculty Innovative Research in Science and Technology (FIRST) internal grant program. We gratefully acknowledge this funding, which supports projects aligned with the University's goals of fostering innovation, advancing impactful research, and expanding opportunities for scholarly growth and collaboration.

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