Unveiling Learners' Interaction Behavior in Virtual Reality Learning Environment

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Abstract: VR is increasingly being utilized in various domains, including education, due to its unique characteristics. Research in this area often relies on physiological sensors, eye-trackers, VR device orientation, human observers, and pre-test and post-test to collect data for quantitative studies and on questionnaires, surveys, and interviews to collect data for qualitative studies in VR Learning. However, there is a dearth of reliable data sources for studying learner behavior in VRLE, and minimal efforts have been made to automatically collect behavioral data in this context. Furthermore, there is a lack of studies that investigate learning processes through the lens of learners' dynamic interaction behavior in VRLE. To address these gaps, we have developed a real-time data collection mechanism that automatically logs learners' interaction behavior in VRLE, including timestamps. This mechanism was deployed in a room-scale VRLE called MaroonVR, and a study was conducted involving undergraduate engineering students. The main objectives of this paper are to identify differences in interaction behavior between high and low performers and to develop an optimal predictor model to predict the learning outcome using learners' interaction behavior in VRLE. Furthermore, we propose that the study's findings can be utilized to model learners' behavior in VR and to provide scaffolding and adaptive personalized VR learning content.

Keywords: Interaction Behavior, VR Learning Environment, Predictor Model, Adaptive Personalized Learning Content

1. Introduction

Virtual Reality (VR) immerses users in a simulated environment, allowing interaction with virtual objects and creating a realistic experience (Wade, Zhang, Bian, Fan, Swanson, Weitlauf,& Sarkar, 2016). Its distinctive qualities of immersion, interaction, and imagination have led to its application in various domains, including automotive, military, healthcare, sports, and education. In education, VR is utilized to teach concepts that are not visible to the naked eye, such as DNA strands (Sharma, Jin, Prabhakaran,& Gans, 2018) and the human circulatory system (Pathan, Rajendran,& Murthy, 2020). It also enables the exploration of inaccessible places like outer space and ancient civilizations. Additionally, VR provides a safe environment for experiencing hazardous scenarios, such as firefighting, welding, and oil refinery operations, which would be dangerous in real life. VR technology has transformed education by offering immersive and engaging learning experiences that enhance understanding and provide practical training opportunities in a wide range of subjects.

The qualities of VR have led to a significant increase in research examining its use in education. Most of the studies were conducted to measure the impact of VR on learning by collecting data from pre-test and post-test. Moreover, the educational researchers used the data collected from self-reported questionnaires, interviews, and surveys (Radianti, Majchrzak, Fromm, & Wohlgenannt, 2020) to measure the user experience, engagement, and usability of the VR systems and to compare VR-aided and VR-non-aided learning systems (Albus, Vogt,& Seufert, 2021). The researchers also used the data collected from the devices such as 1) physiological sensors to assess the affective state of the learners while performing the tasks (Feng, González, Amor, Lovreglio,& Cabrera-Guerrero, 2018), 2) eye trackers to assess the learners' intended area of interest (Wade, Zhang, Bian, Fan, Swanson, Weitlauf,&

Sarkar, 2016) 3) body trackers to adapt the size of the virtual objects with respect to the size of the users, and 4) orientation of the head-mounted displays (HMD) and handheld controllers (HHC) to assess the response time. In addition to the physical devices, human observers were also used to collect data in VRLEs related to the affective state (Feng, González, Amor, Lovreglio,& Cabrera-Guerrero, 2018) and the procedural performance (Santamaría-Bonfil, Ibáñez,Pérez-Ramírez, Arroyo-Figueroa, & Martínez-Álvarez, 2020) of the learners. However, the data provided by human observers are biased due to cognitive, social, and communicative causes. Moreover, the data provided by human observers also need to satisfy inter-rater reliability tests in order to become valid (Olmos-Raya, Ferreira-Cavalcanti, Contero, Castellanos, Giglioli, & Alcañiz, 2018).

All the existing studies reported that using VR technology in the education domain has resulted in a) better learning compared to other learning environments like simulation or Computer Based Learning Environments (CBLE) for procedure learning content (Santamaría-Bonfil, Ibáñez,Pérez-Ramírez, Arroyo-Figueroa, & Martínez-Álvarez, 2020), b) positive impacts such as improvement in learning gain, experience closer to reality, intrinsic motivation, level of interest, skills, and memory retention (Chavez,& Bayona, 2018). Although the existing studies measured the learning gain, the knowledge of how learners interact with VRLE and how they learn from the VR environment is not explored. That is, the existing studies have analyzed the impact of VR intervention on the learning outcomes, but the impact of interaction behavior in VRLE on the learning outcomes is still in its infancy. Hence, the interaction behavior of the learners leading to variation in the performance for different learners is not known. This is mainly due to the non-existence of a data collection mechanism that can log the learners' interaction behavior in VRLE. To address this gap, we developed a mechanism that is able to log all the interaction behavior of the learners in VRLE in real time along with the time stamp (Prakash,& Rajendran, 2022).

The interaction behavioral data collection mechanism we developed was deployed in MaroonVR (Pirker, Holly, Lesjak, Kopf, & Gütl, 2019), a virtual reality learning environment (VRLE) utilized for teaching the physics concept of electromagnetic induction. A study was conducted involving 14 undergraduate students from non-electrical engineering backgrounds, and their interaction behavioral data (IBD) was logged. The participants' interaction with the VRLE resulted in a positive learning gain (Prakash, Shaikh, & Rajendran, 2023). In this paper, we present the extraction of features, such as frequency and duration of action events, to evaluate their impact on the learning outcomes. Furthermore, we discuss the development of an optimal regression predictor model using the features extracted from the data logged in the IBD logger to predict the learning outcome. The predictor model thus developed can be used to early detect the performance of the learners. The knowledge of the early detection of the learners' performance can be used by the designers to design VR learning content that is able to provide the required scaffolding in the form of hints, and feedback to the learners in order to maximize the learning outcome.

The paper is structured as follows. Section 2 discusses the impacts, the learning outcomes, and data collected in the education domain using VR. The research questions addressed by this paper are also presented in section 2. The research methodology is briefed in Section 3 along with various analyses. The results of the analyses are presented in Section 4. The inferences made from the results are discussed in Section 5 along with the conclusion describing the limitations and the guidelines for future work.

2. Literature Review and Background

In this section, we first describe the works related to the impacts of VR on learning. Then we discuss the learning outcomes and the data collected to measure VR impacts and the learning outcomes in the existing studies. We also give a brief overview of the IBD logger and the data logged in it.

2.1 Impacts of VR on Learning

According to Radianti, Majchrzak, Fromm, and Wohlgenannt, (2020), the results obtained from employing immersive VR technology in various educational domains indicate an increase in engagement, time dedicated to learning tasks, and the development of cognitive, psychomotor, and affective skills. VR's ability to offer interaction, immersion (Hamilton, McKechnie, Edgerton, Wilson, 2021), and a first-person perspective (Mikropoulos, & Bellou, 2010) play a significant role in enhancing learning outcomes by providing realistic experiences, fostering intrinsic motivation, and increasing interest in learning. Chavez, and Bayona, (2018) asserted that no literature reported negative effects of using VR in the learning process. Nevertheless, the comprehensive literature review conducted by Hamilton, McKechnie, Edgerton, and Wilson in 2021 revealed a reduction in learning improvement with VR-based learning when contrasted with both desktop learning and conventional classroom learning. Despite the negative learning outcome observed in some studies, potentially attributed to the use of low-end mobile VR tools and the inclusion of factual learning content in VRLE, learners have demonstrated increased motivation and interest in learning when utilizing VR as opposed to traditional approaches and computer-based learning (Makransky, Terkildsen, & Mayer, 2019). The existing studies suggest that VR has a positive impact on learning, particularly in VRLE involving procedural learning content. However, there is a lack of literature that examines the impact of VR learning in relation to the dynamic behavior of the learners in the VRLE.

2.2 Learning Outcomes Measured in VR Learning Environment

Researchers have examined the effects of VR on learning by evaluating various learning outcomes, including cognitive, procedural, and affective skills (Hamilton, McKechnie, Edgerton, Wilson, 2021). Cognitive skills pertain to acquiring declarative knowledge, procedural skills involve psychomotor abilities, and affective skills are related to emotions and attitudes (Hamilton, McKechnie, Edgerton, Wilson, 2021). Among these skills, cognitive skills have received the most attention in VR studies. The evaluation of cognitive skills typically involves assessing knowledge acquisition, retention, and transfer. In existing studies conducted within VR learning environments (VRLE), the assessment of knowledge acquisition is typically done through pre-tests and post-tests, while knowledge retention is evaluated through delayed post-tests. Procedural skills, on the other hand, are assessed by measuring task completion time and the sequential order of accessing intermediate steps to accomplish a task (Feng, González, Amor, Lovreglio,& Cabrera-Guerrero, 2018). Affective skills are evaluated using questionnaires and physiological devices such as electrodermal activity sensors, photoplethysmography sensors, and multichannel physiological sensors (Radianti, Majchrzak, Fromm, & Wohlgenannt, 2020; Feng, González, Amor, Lovreglio,& Cabrera-Guerrero, 2018).

2.3 Data Collection in VR Learning Environment

In order to assess the impact of VR on learning and learning outcomes, data is collected through various methods such as body tracking, performance metrics, physiological responses, questionnaires, and interviews. Body tracking involves analyzing the shape and size of the user's body, and the VR system responds accordingly by adapting the VR environment and the size of objects within it (Olade,Fleming,& Liang, 2020). This may also include VR avatars imitating the body postures and gestures of the users. Performance metric data includes scores from pre-tests, post-tests, and delayed post-tests, as well as data related to task completion time and the number of attempts taken. Physiological sensors are used to collect data on the user's affective state, such as measuring skin conductance levels to evaluate fear and anxiety, heart rate to assess stress, and blood volume pulse amplitude to gauge sympathetic arousal (Feng, González, Amor, Lovreglio,& Cabrera-Guerrero, 2018).

Questionnaires and interviews provide data for quantitative analysis, addressing research questions related to VR usability, user experience, comparisons between VR-aided and non-VR-aided learning, and technology solutions (Hamilton, McKechnie, Edgerton, Wilson, 2021). However, despite the availability of various instruments to collect multimodal data for assessing learning outcomes and system usability, the literature analysis reveals neglect of data related to the learners' interaction behavior.

In non-immersive computer-based learning environments (CBLE), to examine the learners' learning behavior, the data that is logged has the attributes as mouse-wheel, mouse-wheel click, mouse click left and right, key-stroke, and the mouse movements in addition to the exercise, activity, and timestamp (Rajendran, Munshi, Emara, & Biswas, 2018). Similarly, we developed a mechanism that is able to log all the interaction behavior of the learners happening through HHCs in the VRLE along with timestamps in real-time (Prakash, & Rajendran, 2022; Prakash, Shaikh, & Rajendran, 2023). The designed data collection mechanism is suitable for integration with an immersive VR system where the HMD is connected to a desktop computer. The development of the IBD collection mechanism is discussed in Prakash, & Rajendran, (2022) and Prakash, Shaikh, & Rajendran, (2023). The interaction behaviors are logged in a .csv file in the memory of the computer to which the VR HMD is tethered. The IBD logger contains information such as the HHC used (left or right), buttons used (grip, trigger, control buttons, and thumbstick), button actions (clicked, unclicked, pressed, released, touched, and untouched), button pressure (a value between 0 and 1 indicating the pressure applied), thumbstick axis (x and y co-ordinates), thumbstick angle (a value between 0° and 360°), object interacted and timestamps. An excerpt of the IBD logger is shown in Figure 1. The IBD collection mechanism is deployed in MaroonVR (Pirker, Holly, Lesjak, Kopf, & Gütl, 2019), a VRLE used to learn the concepts of electromagnetic induction. Electromagnetic induction is the phenomenon of inducing electromotive force (emf) by moving a magnet in and around the close proximity of a coil. We used three scenes of Maroon VR: 1) Faraday's law experiment (the magnet is grabbed and dragged inside the coil to generate emf), 2) the Falling coil experiment (the magnet and an iron bar are allowed to fall freely inside the coil to observe the emf), and 3) the Perspective scene (learners take the perspective of the magnet and generate emf through their walking). The interactions happening when the coil turns (2, 4, and 6 turns), coil diameter (2, 4, and 6 units), and magnetic field strength are varied using virtual interfaces, and the magnet is grabbed, dragged, and dropped and the walking of the learners in the perspective scene are logged in the IBD logger.

Controller Index	Button	Button Action	Button Pressure	Touchpad Axis	-	Touchpad Angle	Touchpad 2 Axis	-	Touchpad 2 Angle	Object	Time stamp
1	GRIP	unclicked	0	(0.0	0.0)	90	(0.0	0.0)	90	Magnet (VRT	6:14:13
1	GRIP	released	0	(0.0	0.0)	90	(0.0	0.0)	90	Magnet (VRT	6:14:13
1	GRIP	axis changed	0	(0.0	0.0)	90	(0.0	0.0)	90	Magnet (VRT	6:14:13
1	GRIP	untouched	0	(0.0	0.0)	90	(0.0	0.0)	90	Magnet (VRT	6:14:13
1	GRIP	touched	0	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:15
1	GRIP	pressed	1	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:15
1	GRIP	clicked	1	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:15
1	GRIP	axis changed	1	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:15
1	TRIGGER	untouched	0	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:16
1	GRIP	unclicked	0	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:16
1	GRIP	released	0	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:16
1	GRIP	untouched	0	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:16
1	GRIP	axis changed	0	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:16
1	BUTTON ONE	untouched	0	(0.0	0.0)	90	(0.0	0.0)	90	2 Turns Coil	6:14:16

*Figure 1.*An Excerpt of Interaction Behavioral Data Logger

2.4 Research Questions

We measured the impact of VR intervention in learning the concept of electromagnetic induction in the VRLE, MaroonVR as shown in Table 1. In this paper, we have used the interaction behavioral data collected to answer the following research questions.

1. Is there a difference in the interaction behavior between the high and low performers?
2. Is it possible to predict learners' learning outcome based on the actions extracted from their interaction behavior?

3. Research Methodology

3.1 Study Design

The VR system utilized in the study (Meta's Oculus Quest 2) includes a precautionary notice indicating that it is not suitable for individuals under the age of 13. Consequently, we refrained from involving school students in our experimentation. Furthermore, since the learning material is already familiar to electrical engineering students, we excluded them from our study. Instead, we opted to conduct our research with a group of fourteen undergraduate engineering students randomly selected from the computer science engineering department, all of whom possess a non-electrical engineering background. After collecting the details related to demography, and familiarity with VR technology from the study participants, the participants' prior knowledge on the topic of electromagnetic induction was collected using a pre-test. The participants were allowed to play 'First Steps', a VR game for approximately 15 minutes to get familiarized with the controllers of the VR system. Then they experienced the MaroonVR VRLE for approximately 30 minutes. The IBD was collected non-intrusively. After the VR intervention, a post-test was conducted to assess the impact of VRLE on the learning outcome. The experiment was conducted with 1 participant at a time and the total study time for a single participant was approximately 1 hour and 15 minutes.

3.2 Analyses

We measured the impact of VR intervention on the learning outcome in our previous publication (Prakash, Shaikh, & Rajendran, 2023). The evaluated result is shown in Table 1.

Table 1. *Pre-to-post learning gains - all students (n=14)*

Pre-test Score Mean (SD)	Post-test Score Mean (SD)	Normalized Gain (SD)	Effect Size Cohen's d	Paired t-test (p-value)
5.86 (1.75)	7.64 (2.06)	0.42 (0.68)	0.81	3.2 (0.04)

As we intend to explore the impact of interaction behavior in VRLE on the performance, we bifurcated the participants into high and low performers. The participants scoring more than the mean in the post-test are considered high performers and the others as low performers. Accordingly, there are 8 high performers and 6 low performers.

The action events are extracted from the columns of 'Controller Index', 'Button', 'Button Action', and 'Object' of the IBD logger to evaluate the difference in the interaction behavior of the high performers and low performers to answer the first research question. The different action events identified from the logged IBD are shown in the Table 2.

Table 2. *Action Events extracted from the IBD logger and their description*

Action Events	Description
INFO	Reading instruction
NAVIGATE	Teleport, Scene switching
INTERACT_REL	Handling virtual objects such as magnet and iron bar
PERS_WALK	Walking in the perspective scene taking the perspective of magnet
SET_COIL_REL	Setting the turns in the coil between 2 turns, 4 turns and 6 turns
SET_MAG_REL	Varying the magnetic field strength using VR slider interface

In addition to the interactive actions shown in Table 2, the participants also perform actions which are not logged by the IBD collection mechanism such as walking and turning in falling coil scene and faraday scene, learners' utterances, and learners' seeing action. These actions are coined as non-interactive actions.

As mentioned by Prakash, & Rajendran, (2022), the VRLE can be interacted with using specific buttons present in the HHCs such as the Grip button to interact with VR objects and the Trigger button to interact with virtual interfaces. No interactions happen in the VRLE due to the use of irrelevant buttons other than the specified ones and hence they are also kept under the umbrella of non-interactive actions along with the other non-interactive actions such as learners' utterances and seeing.

A comparative analysis is performed between high performers and low performers to examine the duration and frequency of action events. Several tests are conducted to determine if there are significant differences in prior knowledge, knowledge gained after VR intervention, and the extracted features of action events from the IBD logger. Pearson's correlation analysis is utilized to identify action events that exhibit a significant relationship with the learning outcome. Following the correlation analysis, multiple linear regression analysis is conducted using the selected action events to answer the second research question. To determine the optimal predictor model, various information criteria, including the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hannan-Quinn information criterion (HQIC) scores, are evaluated. This predictor model enables the prediction of performance and the provision of personalized feedback, hints, and learning content to enhance the learning outcome.

4. Results and Discussion

The effect of VR intervention on the learning outcome is evaluated from the data collected using the pre-test and post-test (Prakash, Shaikh, & Rajendran, 2023). We measured the normalized learning gain and effect size to understand the impact of the effect produced by VR intervention. We also found using a paired t-test that the post-test score was significantly higher than the pre-test score with $t(13)=3.2$, $p=0.04$, and identified that the significant learning outcome resulted was due to VR intervention (see Table 1).

4.1 Research Question 1: Is there a difference in the interaction behavior between the high and low performers?

Participants are divided into high and low performers to examine how VRLE interaction behavior influences the learning outcome. The homogeneity between the high performers and low performers before VR intervention is assessed using Levene's test. The results of Levene's test indicate that there is no significant difference in homogeneity between the high performers and low performers ($p < .05$) prior to VR intervention ($F = 0.545$, p-value = .474). Therefore, the requirement for homogeneity is satisfied.

The significant differences between the high performers and low performers on various parameters were evaluated using a series of Mann-Whiteney U-tests. The results are tabulated in Table 3.

Table 3. *Significance test results for the difference between the high and low performers*

	Pre-test Score Mean (SD)	VR Intervention Duration Mean (SD)	Post-test Score Mean (SD)
Low Performers	5.33 (1.51)	2256.17 (649.17)	5.67 (1.21)
High Performers	6.25 (1.91)	1743.25 (294.5)	9.13 (0.99)
Mann-Whiteney U Test Score	U=16.5, and p-value=.368	U=13, and p-value=.174	**U=0,and p-value= .002***

**-significant at p-value < .05*

Despite no significant difference in prior knowledge (Mann-Whitney test on pre-test scores), the duration of VR intervention (Mann-Whitney test on VR intervention duration), and the homogeneity of pre-test scores between high and low performers (Levene's test), there is a significant difference in the learning outcome (Mann-Whitney test on post-test scores). This suggests that the variation in learning outcomes among participants is attributed to differences in their interaction behavior within the VRLE. Consequently, various action events, along with their duration and frequency, were extracted from the IBD logger to investigate the impact of participants' interaction behavior on the learning outcome.

Although there is no significant difference in the duration spent in the VRLE between high performers and low performers, we noticed that high performers exhibited a higher number of relevant interactive actions and spent more time engaging in those actions compared to low performers. Relevant interactive actions are the action events defined in Table 2. We calculated $Relevant\ Interaction\ Duration\ \% = \frac{Total\ Duration\ of\ action\ events}{Total\ Duration\ of\ VR\ Intervention}$ and $Relevant\ Interaction\ Frequency\ \% = \frac{Sum\ of\ frequency\ of\ action\ events}{Sum\ of\ frequency\ of\ (action\ events + non-interactive\ actions)}$.

The one-tailed Mann-Whitney U test conducted on the Relevant Interaction Duration % revealed a significant difference at p<.05 between high performers and low performers, U = 9, p = 0.031. However, the one-tailed Mann-Whitney U test conducted on the Relevant Interaction Frequency % showed no significant difference at p<.05 between high performers and low performers, U = 24, p = 0.476. Thus it is found that there is a significant difference in the duration of relevant interaction between the high and low performers. Whereas, no significant difference is observed in the number of interactions between the high and low performers. The descriptive statistics of the Relevant Interaction Duration % and the Relevant Interaction frequency % for the high performers and low performers are shown in the Figure 2 as a box plot.

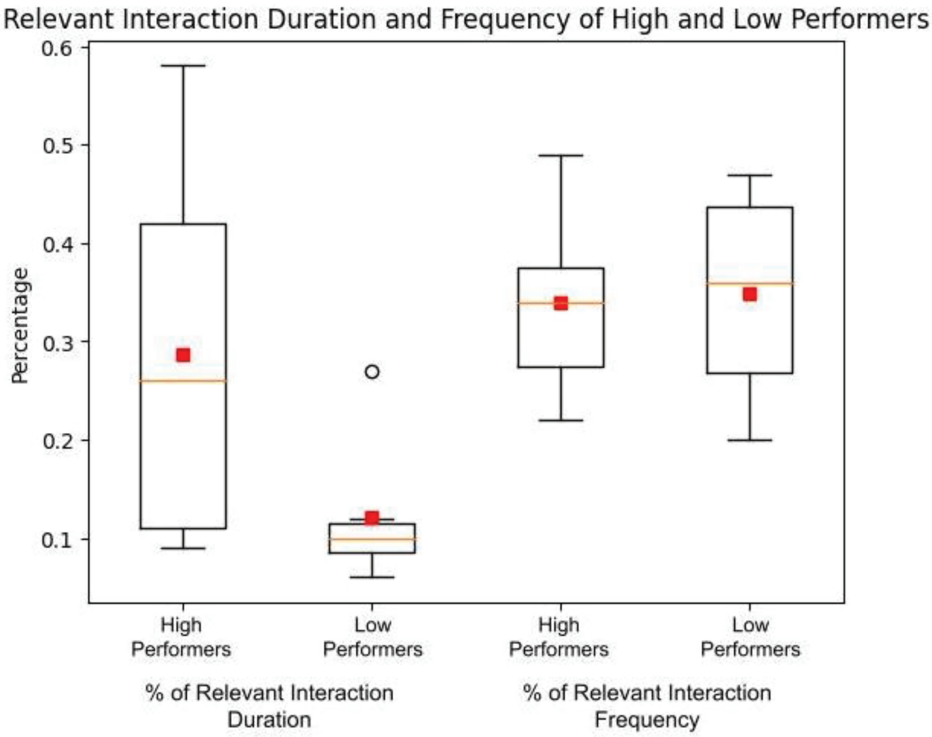

Figure 2. Difference in the interaction behavior between the high and low performers

4.2 Research Question 2: Is it possible to predict learners' learning outcome based on the actions extracted from their interaction behavior?

4.2.1 Correlation Analysis

The difference in the learning outcome between high performers and low performers can be attributed to the interaction behavior of the learners within the VRLE, as indicated by the results of the Mann-Whitney test and Levene's test. To further explore this relationship, we conducted a Pearson correlation analysis between the action events identified from the IBD logger and the post-test score. The results of the correlation analysis are presented in Table 4.

Table 4. *Correlation Analysis Results (Bolded Variables Indicate Significant Correlation with Post-Test Score)*

Learning Outcome Variable	Action events	Pearson's r	p-value
Post-test score	**Total VR Intervention Duration**	**-0.695**	**.006**
	INFO_DUR	0.196	.503
	NAVIGATE_REL_DUR	-0.144	.623
	INTERACT_REL_DUR	-0.068	.82
	PERS_WALK_DUR	-0.116	.693
	Total Number of Interactions	-0.302	.296
	NAVIGATE_REL_FREQ	**-0.626**	**.017**
	SET_COIL_REL_FREQ	-0.487	.078
	SET_MAG_REL_FREQ	**-0.662**	**.01**
	INTERACT_REL_FREQ	-0.344	.228
	PERS_WALK_FREQ	-0.125	.673
	Non-Interactive Action Duration	**-0.654**	**.011**

From the Table 4, the variables Total VR Intervention Duration, NAVIGATE_REL_FREQ, and SET_MAG_REL_FREQ show a significant negative correlation with the post-test score, while the variable Non-Interactive Action Duration exhibits a significant positive correlation. An increase in the values of the negatively correlated variables is associated with a decrease in the post-test score, whereas an increase in the value of the positively correlated variable is linked to an increase in the post-test score.

4.2.2 Regression Analysis

The regression analysis was conducted using the variables having a higher correlation with the post-test score. The forward feature selection algorithm was used to develop multiple linear regression models.

Table 5. *Scores of various scales to choose optimum predictor model to predict learning outcome using action events of interaction behavior*

Regression Model	No. of Predictors	AIC	BIC	HQIC	R2	RMSE
Non-Interactive Action Duration, NAVIGATE_REL_FREQ, SET_MAG_REL_FREQ	3	**47.669**	**50.226**	-31.906	**0.555**	**1.373**
Total VR Intervention Duration, Non-Interactive Action Duration, NAVIGATE_REL_FREQ, SET_MAG_REL_FREQ	4	49.625	52.821	**-29.921**	0.360	1.646

To find the best regression model out of the various models developed we evaluated the scores of AIC, BIC, and HQIC (Ventura, M., Saulo, H., Leiva, V., & Monsueto, S., 2019). The model having the minimum score of AIC, BIC, and HQIC is chosen as the optimum model to predict the learning outcome. The AIC and BIC scores are low for the model having the interaction behavior variables such as Non-Interactive Action Duration, NAVIGATE_REL_FREQ, and SET_MAG_REL_FREQ as predictors is considered as Model 1. Whereas, a minimum HQIC score is observed for the model having the variables such as Total VR Intervention Duration, Non-Interactive Action Duration, NAVIGATE_REL_FREQ, and SET_MAG_REL_FREQ as predictors is considered as Model 2. Hence to choose the optimum regression model we evaluated the performance of the two models. The performance of the regression models was evaluated using a training set size of 66% and a test set size of 34%, with 10 iterations of random sampling. Model 1, which used Non-Interactive Action Duration, NAVIGATE_REL_FREQ, and SET_MAG_REL_FREQ as predictors, demonstrated higher R2 (0.555) and lower root mean square error (RMSE) (1.373) compared to Model 2 (R2=0.360, RMSE=1.646). Thus, Model 1 was chosen as the optimum regression model to predict the learning outcome. The scores of various information criterion of the regression models is shown in Table 5.

The result of the multiple regression analysis done on the model 1 chosen as the optimum model is shown in Table 6. The value of $R^2 = 0.55$ for the optimal model indicates that 55% of the variance is explained by the model. The B value in the Table 6 indicates the average change in the post-test score (outcome variable) by 1 unit when the corresponding predictor variables are changed by the given value keeping all the other variables constant. Furthermore, the multicollinearity assumption was tested, and the results indicated that the variance inflation factor (VIF) of all predictor variables was below 10, suggesting that multicollinearity was not violated.

Table 6. *Performance of the optimum predictor model*

Variables	R2	B	p-value	VIF
Non-Interactive Action Duration	0.555	-0.001	0.02	0.244
NAVIGATE_REL_FREQ		-0.026	0.044	0.181
SET_MAG_REL_FREQ		-0.241	0.4	0.182

5. Conclusion

This study examined the interaction behavior of learners in VRLE and identified differences in the duration and frequency of action events between high performers and low performers. The duration of relevant actions performed by participants was found to significantly impact the post-test scores, differentiating high performers from low performers. Additionally, an optimal predictor model was developed using variables related to learners' interaction behavior, including Non-Interactive Action Duration, NAVIGATE_REL_FREQ, and SET_MAG_REL_FREQ. The predictor model demonstrated performance with an R^2 value of 0.555. The study ensured that the variables in the model did not violate the multicollinearity assumption.

Despite the fact that the study was effective in collecting IBD and fitting it using a linear regression model, it was carried out with a lower sample size of 14 patients. Hence, further study with a larger sample size is needed to make the regression model more predictable and transportable. In addition, further work is also required to add the information related to the learner’s views and the pace of interactive actions as important traits in understanding the interaction behavior of the learners in VRLE.

The current research paper has contributed to 1) identifying the key difference between the high and low performers from the perspective of interaction behavior in VRLE, 2) designing a predictor model using significant variables of action events extracted from the interaction behavior, and 3) measuring the impact of VR on learning the subject area of electronics engineering as VR studies in electronics engineering are limited. In addition, this study suggests further implications for mining behavioral patterns from the IBD and analyzing the differences in behavioral patterns between high and low performers. Moreover, the study proposes that the interaction behavior comprehended with the performance of the learners can be used by the developers to design VR learner models that can offer adaptive and individualized feedback, hints, and learning content. As a next step, we aim to expand the scope by developing a VR-based Adaptive Tutoring System based on these concepts.

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