# Examining Different Affective Factors in Learning with Virtual Reality

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**Abstract:** This study aims to examine how prior knowledge and affective factors of virtual reality environments predict science learning achievement through the mediation of learning engagement. Ninety-two sixth-grade students in Taiwan were recruited in this study. Data were analyzed through partial least squares structural equation modeling (PLS-SEM). The results showed that prior knowledge negatively predicted presence and control and active learning. Presence, control and active learning positively predicted learning engagement (behavioral engagement, cognitive engagement, emotional engagement). Cognitive fatigue was found to negatively predict emotional engagement and science learning achievement. Implications and suggestions for future research were addressed in the study.

**Keywords:** presence, cognitive fatigue, control and active learning, learning engagement, virtual reality

## 1. Introduction

In the modern education landscape, digital learning platforms and advanced technological tools have completely transformed the nature of learning. With the continuous evolution of instructional technology, virtual reality (VR) has become a part of innovative educational approaches, the sense of realism in the learning environment has continuously improved and offers students unprecedented levels of engagement and interaction. By exploring, manipulating, and experimenting within a virtual environment, learners can obtain immersive learning experiences (Radianti et al., 2020).

In the VR learning environment, students not only have the ability to freely explore and experience in a VR environment but also have the freedom to control the pace and content of their learning. Previous research has shown that if students have a higher degree of control in learning, they also achieve better learning outcomes and satisfaction (Jang et al., 2017; Lee et al., 2010). Nevertheless, prolonged exposure to digital learning environments, especially when engaging in learning within virtual contexts, may lead to an overwhelming cognitive load, potentially negatively impacting learning outcomes (Parong & Mayer, 2018). Studies have also shown that users have reported experiencing cognitive fatigue after prolonged use (Cummings & Bailenson, 2016; Munafo et al., 2017). However, there is still a lack of research regarding the effect of cognitive fatigue and its relationship with other factors in the context of VR learning environments.

Makransky and Petersen (2021) have developed the cognitive affective model of immersive learning (CAMIL) illustrating the relationships among VR affordances, affective and cognitive factors, and learning outcomes. Among the different research directions, it was suggested that future study can investigate the impact of external factors on personal traits or dispositions. Therefore, the research purpose of this study is to explore the effects of learners' prior knowledge and other affective factors of VR environments on their learning engagement and learning outcomes in the VR learning environment. A model was developed describing the hypothesized relationship among the variables used in this study based on the literature mentioned above (see Figure 1). Prior knowledge is hypothesized to positively predict students' affective factors of VR environments (Kim et al., 2021). Among the affective factors, presence and control and active learning are hypothesized to be positively predict learning engagement and learning outcomes (Lee et al., 2010; Purarjomandlangrudi & Chen, 2020). On the contrary, cognitive fatigue is hypothesized to be negatively predict learning engagement and learning outcomes (Hwang et al., 2019). Learning engagement is hypothesized to be positively predict learning outcomes (Liu et al., 2022).

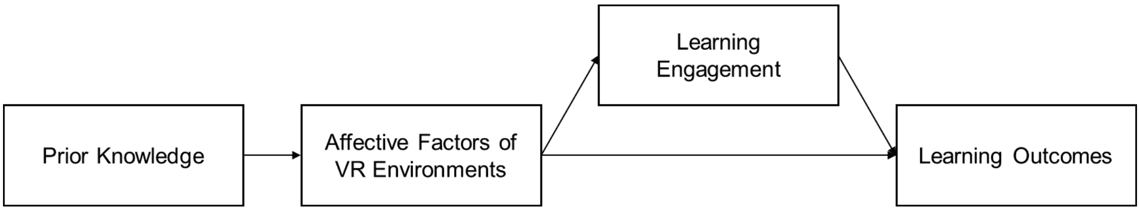


*Figure 1*. The hypothesized model regarding relationships among prior knowledge, affective factors of VR environments, learning engagement, and learning outcomes.

## *1.1 Affective Factors of VR environments*

In the following, the effects of the affective factors in VR environments were discussed, including presence, cognitive fatigue, and control and active learning.

### *1.1.1 Presence*

Presence is the sense of being in one place, which is a psychological state or subjective perception in which even though part of or all of an individual's current experience is generated by the system (Lee et al., 2010). In VR, presence acts as an affordance, leading to deeply immersive experiences (Makransky & Petersen, 2021).

Empirical research has highlighted the relationship between a user's prior knowledge and their sense of presence in virtual environments. For instance, participants with higher levels of prior knowledge related to the content of a virtual environment reported a deeper sense of immersion and spatial presence (Kim et al., 2021). Purarjomandlangrudi and Chen (2020) examined students' sense of presence in a virtual classroom and its subsequent influence on their engagement levels. The findings demonstrated that students who reported a heightened sense of presence were significantly more engaged in their learning tasks than those who felt detached. Studies have also shown that students who perceived a higher presence in the virtual environment might have higher learning outcomes (Lee et al., 2010). However, studies have also shown that higher immersion leads to higher cognitive load (Parong & Mayer, 2018). Researchers have also concluded that students in high-immersion VR environments would have a higher sense of presence but less learning (Makransky et al., 2019).

### *1.1.2 Cognitive fatigue*

Cognitive fatigue, also known as mental fatigue, refers to the decline in cognitive performance and efficiency after prolonged periods of cognitive activity. It manifests as reduced attention, slower reaction times, and increased errors (Boksem et al., 2005). Studies have shown that an increase of cognitive fatigue decreased cognitive control (Lorist et al., 2005) and high-level information processing (Tanaka et al., 2014). Researchers indicated that when the learning material required students' cognitive effort in a limited amount of time might lead to increasing cognitive fatigue, thereby affecting performance (Hwang et al., 2019).

### *1.1.3 Control and active learning*

Control and active learning refer to leveraging VR technology could empower learners to actively engage with and shape their own learning experiences within a virtual environment

(Lee et al., 2010). Studies have shown that students with higher level of control and active learning might enhance their learning engagement, achievement, and retention of knowledge (Deslauriers et al., 2019; Freeman et al., 2014). Previous studies demonstrated that the level of control and active learning could lead to increased engagement, motivation, and learning outcomes among students (Makransky & Lilleholt, 2018).

### *1.2 Learning engagement*

Learning engagement refers to the dynamic and multifaceted involvement of students in the learning process (Furrer & Skinner, 2003). Cognitive, emotional, and behavioral dimensions are typically regarded as being a part of learning engagement (Fredricks et al., 2004). *Cognitive engagement* refers to the mental effort, concentration, and active participation that students invest in learning tasks and academic activities. The observable actions and behaviors that students exhibit in the learning process, such as participation in classroom activities or putting effort in completing assignments, is referred to as *behavioral engagement*. *Emotional engagement* refers to the affective or emotional reaction of a student's involvement in learning, including different emotions, such as enjoyment or boredom.

Previous studies discovered that engagement in school-related tasks, including cognitive and behavioral engagement, predicts academic achievement and educational attainment over time (Fredricks et al., 2004; Wang & Eccles, 2013). In the context of VR learning environment, students were found to demonstrated higher learning achievement and learning engagement (Akman & Çakır, 2023).

## 2. Method

### *2.1 The VR learning materials*

This learning material was designed by our research team for elementary school students between 5th to 6th grades to learn concepts related to water, including water in the atmosphere, the structure of plants, the lives of animals, and supplementary knowledge of science. With the guidance of a virtual agent and the visualization of microscopic objects and natural phenomena, students could learn water-related knowledge by exploring the VR learning material.

The VR learning material consisted of five scenes, including pre-training and four different seasons. Students become familiar with the operation and have a preliminary understanding of the content of this learning material by interacting with content in the pre-training scene. A self-evaluation system was also embedded in the VR learning material. After students finished learning science knowledge of each scene, there would be questions for them to practice. Students could check their learning status with immediate feedback and comments after they answered each question.

### *2.2 Participants and procedure*

Data were collected from 92 6th-grade elementary students with ages between 11 to 12 in Taiwan. Among these students, there were 35 males (38%) and 57 females (62%). Before the experiment, students were acknowledged the purpose of the experiment and only the students who volunteered to participate were recruited. Students first completed a test of science prior knowledge to assess their prior knowledge of the water-related concepts before experiencing the VR learning activity for a maximum of 30 minutes. Subsequently, students were asked to complete a science post-test and post-survey to measure their presence, cognitive fatigue, control and active learning, and learning engagement.

### *2.3 Instruments*

Four questionnaires were designed to measure students' presence, cognitive fatigue, control and active learning, and learning engagement. A test of prior knowledge and a science learning achievement test were developed to test students' understanding of the concepts related to water.

#### *2.3.1 Presence questionnaire*

Presence questionnaire, adopted from Schubert et al. (2001), consisted of *spatial presence (four items)*, *involvement (three items)*, and *experienced realness (one item)*. Spatial presence, defined as the perception that the user's body is actually located in the virtual space, includes items such as "I felt present in the virtual space." The items in involvement measured how much attention the VR learning activity draws to the user, and how much the user still pays attention to the real world, sample item includes "I concentrated only on the virtual space." Experienced realness was defined as the realness the user felt between VR learning activity and reality, including items such as "My experience in the virtual environment is the same as my experience in the real world." Participants responded on a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

#### *2.3.2 Cognitive fatigue scale*

Cognitive fatigue was defined as decreased cognitive resources and cognitive function over time due to sustained cognitive demands (Trejo et al., 2005). Cognitive fatigue scale, adapted from Hwang et al. (2019), consisted of four items in this study, and the sample item includes "My concentration would disappear very quickly when I experienced the VR learning activity." Participants responded on a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Past study has reported good reliability of the scale ($\alpha = 0.94$) (Hwang et al., 2019).

#### *2.3.3 Control and active learning scale*

Control and active learning was defined as the level of autonomy learners were allowed in the learning environment (Lee et al., 2022). Control and active learning scale, adopted from Lee et al. (2022), consisted of five items. Participants responded on a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Sample item of the scale includes "This type of VR learning activity allows me to have more control over my own learning." Past study has reported good reliability of the scale ($\alpha = 0.88$) (Lee et al., 2010).

#### *2.3.4 Learning engagement scale*

Learning engagement scale, adopted from Lee et al. (2021), comprises three sub-scales: *behavioral engagement* (five items), *cognitive engagement* (four items), *and emotional engagement* (four items). Although the original scale encompassed social engagement, the sub-scale was not included since there was no peer interaction in this study. Behavioral engagement, defined as the behavior related to academic achievement, includes items such as "I keep trying even if the learning activity is hard." Cognitive engagement was defined as the effort, including meta-cognition and self-regulation, to understand learning content. A sample item of cognitive engagement includes "I think about different ways to solve a problem." Emotional engagement was defined as the emotional responses to learning activities, including interest, enjoyment, and perceived value of learning. Sample item of emotional engagement includes "I feel good when I am doing this learning activity." Participants responded on a Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Past study has reported good reliabilities of the factors (behavioral engagement: $\alpha = 0.85$; cognitive engagement: $\alpha = 0.88$; emotional engagement: $\alpha = 0.90$) (Lee et al., 2021).

#### 2.3.5 Science achievement test

The multiple-choice assessments were designed based on the content in the VR learning material to evaluate students' understanding of the concepts related to water, such as the different states of water, the formation of frost and fog, etc. The science prior knowledge test (8 items) and learning achievement test (13 items) were used to measure students' prior knowledge and their learning outcomes after learning through the VR learning material.

### 2.4 Data analysis

In this study, partial least squares structural equation modeling (PLS-SEM) was used to analyze the data. PLS-SEM, considered to be the second generation of multivariate analysis for verifying a relationship between variables, is suitable for analyzing small sample sizes of data and does not need normal data distribution (Hair et al., 2021).

In this study, presence was treated as a formative construct due to the independent contribution of the items, while other variables were considered as reflective constructs. In a reflective construct, the latent variable causes the observed indicators, which means that any change in the construct would result in changes in its indicators. On the contrary, the observed indicators cause or form the latent variable is a formative construct, which means that the construct is determined by its indicators. Unlike reflective constructs, the indicators in formative construct do not necessarily have to be correlated, and they each contribute uniquely to the formative construct. PLS-SEM also has the advantage to contain both reflective and formative constructs in a model (Hair et al., 2021).

The evaluation of PLS-SEM begins with the measurement model where each indicator's factor loading of reflective constructs should ideally surpass 0.7 for reliability. Additionally, the composite reliability (CR) of constructs should exceed 0.7, while their average variance extracted (AVE) should be above 0.5, ensuring convergent validity. For discriminant validity, the square root of a construct's AVE should be greater than its highest correlation with any other construct, with methods like the Fornell-Larcker criterion often used for further validation. The formative constructs were evaluated by assessing variance inflation factor values (VIF), and outer weights.

Transitioning to the structural model, the coefficient of determination ($R^2$) is scrutinized, where values above 0.75 indicate strong explanatory power. Path coefficients are crucial, with significance denoting impactful relationships among constructs. Effect sizes, represented as $f^2$, should ideally exhibit values of 0.02, 0.15, or 0.35 for small, medium, or large effects, respectively. Predictive relevance, measured by $Q^2$, becomes vital, with values greater than zero signifying model relevance.

## 3. Results

### 3.1 Measurement model

The quality of the measurement model was examined by construct reliabilities and construct validities. The Cronbach's alpha values and the composite reliability (CR) values were tested to verify the internal consistency of the indicators of each construct (Hair et al., 2021). As shown in Table 1, Cronbach's alpha values of the constructs were between 0.86 to 0.98, which were above the suggested value of 0.70. Additionally, the CR values of the constructs were between 0.91 to 0.98, which also met the requirement of being greater than 0.70. These results show that the measurement model had sufficient reliability and the internal consistency of the indicators for each construct was good.

Convergent validity and discriminant validity were assessed to verify whether the measurements effectively reflected the corresponding measured constructs. Factor loadings of indicators and the average variance extracted (AVE) of constructs were used to validate the convergent validity of the measurements. The factor loadings of the individual items and the AVE values of the constructs were all above 0.7, which is higher than the suggested value (Hair et al., 2021). BEng 1 was deleted since the value of its factor loadings was below 0.7. These results showed adequate convergent validity.

Table 1. *Confirmatory Factor Analyses and Reliabilities of Cognitive Fatigue, Control and Active Learning, and Learning Engagement.*

| | Mean | *SD* | Factor loadings | Cronbach's alpha | CR | AVE |
|---|---|---|---|---|---|---|
| **Cognitive Fatigue (CF)** | | | | 0.97 | 0.97 | 0.91 |
| CF 1 | 2.34 | 1.23 | 0.95 | | | |
| CF 2 | 2.47 | 1.24 | 0.93 | | | |
| CF 3 | 2.43 | 1.17 | 0.97 | | | |
| CF 4 | 2.42 | 1.28 | 0.95 | | | |
| **Control and Active Learning (CAL)** | | | | 0.98 | 0.98 | 0.91 |
| CAL 1 | 3.95 | 0.86 | 0.96 | | | |
| CAL 2 | 3.90 | 0.87 | 0.95 | | | |
| CAL 3 | 3.93 | 0.82 | 0.97 | | | |
| CAL 4 | 3.88 | 0.87 | 0.95 | | | |
| CAL 5 | 4.02 | 0.86 | 0.93 | | | |
| **Behavioral Engagement (BEng)** | | | | 0.86 | 0.91 | 0.71 |
| BEng 2 | 3.84 | 0.86 | 0.82 | | | |
| BEng 3 | 3.97 | 0.89 | 0.90 | | | |
| BEng 4 | 3.85 | 0.94 | 0.90 | | | |
| BEng 5 | 4.11 | 0.81 | 0.74 | | | |
| **Cognitive Engagement (CEng)** | | | | 0.89 | 0.92 | 0.74 |
| CEng 1 | 4.02 | 0.85 | 0.88 | | | |
| CEng 2 | 3.91 | 0.84 | 0.88 | | | |
| CEng 3 | 3.91 | 0.87 | 0.81 | | | |
| CEng 4 | 3.86 | 0.88 | 0.88 | | | |
| **Emotional Engagement (EEng)** | | | | 0.90 | 0.93 | 0.78 |
| EEng 1 | 4.17 | 0.90 | 0.90 | | | |
| EEng 2 | 3.76 | 0.97 | 0.81 | | | |
| EEng 3 | 3.95 | 0.90 | 0.91 | | | |
| EEng 4 | 4.20 | 0.86 | 0.90 | | | |

The Fornell-Larcker criterion and cross loadings were measured to verify discriminant validity, which indicates the degree to which each construct in the resulting model is distinct from the others (Hair et al., 2021). The cross loadings of measurement variables are suggested to be higher than the related latent variable. The square root of the AVE value of each variable should also be higher than 0.5 and larger than the Pearson's correlation coefficient between the two variables. All cross loadings of the items were higher than each related latent variable. The AVE value of each variable (0.84 - 0.95) achieved the standard as well. In accordance with Hair et al. (2021), the results indicated that the discriminant validity of the variables was verified.

In this study, presence was considered as formative construct. By using a global single item for redundancy analysis, the convergent validity of formative constructs was evaluated by examining its correlation with an alternative measure of the construct. The result of redundancy analysis for convergent validity of presence was 0.85, which was above the suggested value of 0.8. Variance inflation factor (VIF), outer weights, and outer loadings were assessed to verify the collinearity, significance, and relevance of formative items. The acceptable collinearity and adequate construct validity were signified by VIF values less than 5, which indicated that an item's contribution to the primary latent construct was unique (Hair et al., 2021). The outer weight of an item determines its relative importance in formative constructs, and the outer loadings of an item determines its absolute importance to the construct (Hair et al., 2021). An item was kept in the measurement model if it had a significant outer weight ($p < .05$), or if its outer loadings was higher than 0.5. Items that did not meet these criteria were further evaluated based on the significance of their outer loadings. An item was ultimately removed from the model if its outer loading was lower than 0.5 and not significant.

### *3.2 Structural model*

PLS-SEM was used to test the hypotheses proposed in this study, which included the relationships among prior knowledge, affective factors of VR environments (presence, cognitive fatigue, control and active learning), learning engagement (behavioral engagement, cognitive engagement, emotional engagement), and learning outcomes (science learning achievement). The paths with statistical significance ($p < .05$) are shown in Figure 2. The results indicated that prior knowledge negatively predicted presence ($\beta$ = -0.24, $p < .05$), control and active learning ($\beta$ = -0.21, $p < .05$). Presence positively predicted behavioral engagement ($\beta$ = 0.44, $p < .001$), cognitive engagement ($\beta$ = 0.40, $p < .001$), and emotional engagement ($\beta$ = 0.38, $p < .001$). Cognitive fatigue negatively predicted emotional engagement ($\beta$ = -0.22, $p < .001$) and science learning achievement ($\beta$ = -0.25, $p < .05$). Control and active learning positively predicted behavioral engagement ($\beta$ = 0.41, $p < .001$), cognitive engagement ($\beta$ = 0.44, $p < .001$), and emotional engagement ($\beta$ = 0.44, $p < .001$).

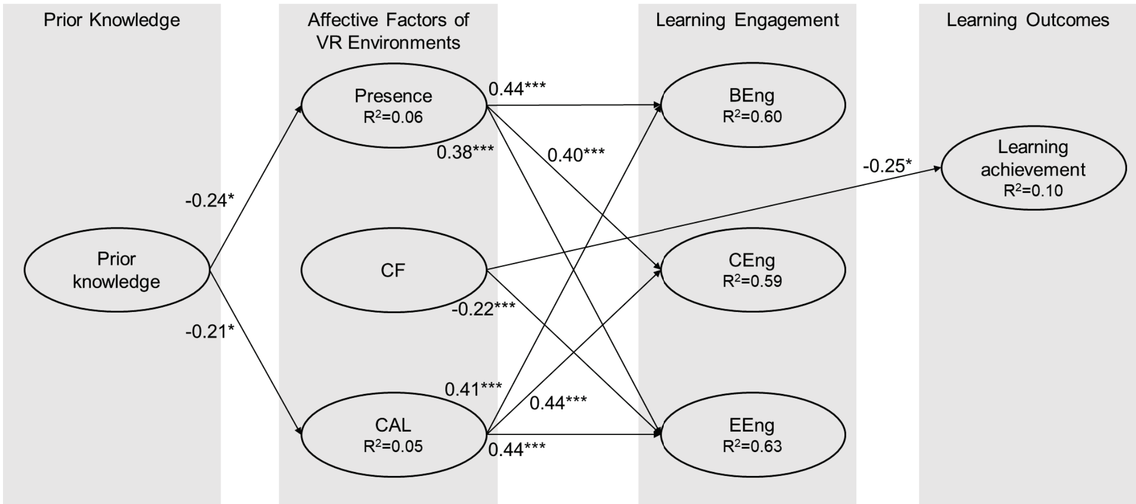


*Figure 2*. Structural Model Results of Prior Knowledge, Affective Factors of VR Environments, Learning Engagement, and Learning Outcomes (only significant paths are shown). (CF=Cognitive Fatigue, CAL=Control and Active Learning, BEng=Behavioral Engagement, CEng=Cognitive Engagement, EEng=Emotional Engagement)

### *3.3 Mediation*

As shown in Table 2, control and active learning played significant mediating role between presence and learning engagement. Control and active learning mediated the relationship between presence and behavioral engagement ($\beta$ = -0.09, $p < .05$), cognitive engagement ($\beta$ = -0.09, $p < .05$), and emotional engagement ($\beta$ = -0.09, $p < .05$).

Table 2. *Mediation Analyses Results of the Hypothesized Model (only significant paths are shown).*

| Path | $\beta$ | $t$ | $p$ |
|---|---|---|---|
| Prior knowledge → CAL → BEng | -0.09 | 2.02 | .044* |
| Prior knowledge → CAL → CEng | -0.09 | 1.99 | .046* |
| Prior knowledge → CAL → EEng | -0.09 | 2.09 | .037* |

*$p$<.05; CAL=Control and Active Learning; BEng=Behavioral Engagement; CEng=Cognitive Engagement; EEng=Emotional Engagement.

## 4. Discussion

According to the model analysis, it was found that science learning achievement was negatively predicted by cognitive fatigue. In other words, an increase in students' cognitive fatigue decreased their learning performances. Additionally, cognitive fatigue was found to negatively predict emotional engagement, which referred to the increase of students' cognitive fatigue would decrease their emotional response to learning activities. The information given in the learning material and the questions after exploring every scene, which required students' sustained cognitive demands, might gradually increase their cognitive fatigue. Moreover, students had to finish the post-test assessment right after experiencing the learning material. Students might not find the learning activities interesting and not willing to engage in it due to the reasons mentioned above. It is suggested that researchers could divide experiment into several learning stages, and give students time to rest between these stages in order to reduce their perception of cognitive fatigue, improve their learning performance and willingness of engaging in the learning activities.

On the contrary, learning engagement was found to be positively predicted by presence and control and active learning. These results showed similarities with the results of Purarjomandlangrudi and Chen (2020), which indicated that students with higher sense of presence might be more engaged in their learning activities than those who felt detached. However, the findings showed that students' prior knowledge could negatively predict their sense of presence and control and active learning, which showed differences from the results shown in Kim et al. (2021). It is suggested future studies could deepen the exploration of the relationships between students' prior knowledge and their sense of presence with different ages of students.

Furthermore, control and active learning was found to mediate the relationships between prior knowledge and learning engagement. In other words, learners with lower prior knowledge might not only perceive higher level of autonomy over their learning, but also increase their interactions with the learning material. It is recommended that in the future, such learning materials be provided to students with lower prior knowledge, as they can potentially derive greater benefits.

Finally, presence was treated as a formative construct in this study, while most of the studies treated presence as a reflective construct (e.g., Makransky et al., 2019). In future research, we suggest investigating presence as a formative construct, considering its potential to offer deeper insights into the dynamic interplay of its components. Additionally, contextual variations and qualitative inquiries could provide a comprehensive understanding of how learners experience presence in diverse educational settings, ultimately enriching the theoretical frameworks and pedagogical strategies.

## 5. Conclusion

A model was proposed in this study suggesting the relationships among prior knowledge, affective factors of VR environments (presence, cognitive fatigue, control and active learning), learning engagement (behavioral engagement, cognitive engagement, emotional engagement), and learning outcomes (science learning achievement). The effects of prior knowledge and cognitive fatigue were highlighted due to the differences from previous studies and the lack of empirical evidence. Finally, future studies are suggested to consider treating presence as a formative rather than a reflective construct.

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# W08

## The 11th Workshop on Technology-Enhanced STEM Education