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High School Students' Sentiments and Outcomes in FossilSketch Learning Activities

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Abstract
FossilSketch was developed to address the lack of resources in undergraduate education for micropaleontology - the study of microfossils used to understand past environments and aid in oil and gas exploration. Traditionally, training in micropaleontology requires specialized resources, such as microscopes and fossil materials. In such training, personalized instructor feedback may require significant time and thus only be available in small classes. As a result, most institutions offer very limited micropaleontology exposure to students. FossilSketch was developed to overcome this hurdle by providing accessible and engaging activities for learning micropaleontology. Its features include educational videos, step-by-step exercises, and interactive mini-games that provide real-time automatic feedback, enabling independent learning while offering instructors tools to manage and track progress. In this study, we introduced FossilSketch to high school students during an outreach program, SeaCamp 2024. We collected data that included students' outcomes (scores) in different activities. Also, the data were collected using a survey that reflect students' perceptions towards studying micropaleontology using FossilSketch activities. We calculated the sentiment value of students' perception using the Valence Aware Dictionary and sEntiment Reasoner (VADER) from the survey data. The following research question was addressed in the paper: What aspects of students' learning outcomes from FossilSketch's activities shaped their sentiments toward studying micropaleontology? To answer this research question, we analyzed the data using Spearman's correlation and XGBoost's feature importance values. Correlational analysis showed that three aspects of FossilSketch's activities showed a significant relationship with students' sentiments toward learning more about micropaleontology: 1) Morphotype Matching Mini-Game Attempt Count (p=0.001), 2) Ostracod Orientation Mini-Game Average Score (p=0.041), and 3) Ostracod Outline Mini-Game Average Score (p=0.035). The Total Average Score per Attempt of an Activity had the highest value in XGBoost's list of feature importance values while negatively correlated with students' sentiments. Our analysis showed that students participating in activities more frequently had more positive sentiments towards learning more about micropaleontology, even though they did not have higher average scores per activity attempt. The results of this study are novel and provide information on the effectiveness of FossilSketch for outreach activities from the perspectives of high school students.

Introduction

Micropaleontology is a branch of geoscience that studies microfossils, which are remains of ancient organisms preserved in sediments that are very small in size, 2 mm or less [1][2]. Microfossils provide unique insights into the past regarding the environments and climates of specific geological periods [1][3][4]. These insights can also be utilized to help with the search for oil and sediment age identification [1][5][6]. Given the critical importance of microfossils and their applications across diverse fields, universities must prioritize training the next generation of scientists by integrating micropaleontology into undergraduate curricula and preparing students for this essential discipline [7]. Importantly, teaching these concepts requires the creation of authentic and active learning environments [8][9].

The creation of active learning environments is important as micropaleontology is a difficult topic for instructors to teach and for students to learn [8][9][10]. Also, teaching micropaleontology is inherently complex, requiring access to critical resources such as high-quality microscopes, well-preserved fossil specimens, and knowledgeable instructors capable of providing personalized feedback [9]. Many institutions currently face a shortage of these resources, making it difficult for instructors to create an active learning environment when teaching micropaleontology [11][12][13] and for students to develop a deeper understanding of micropaleontology concepts [9]. Similarly, students entering the workforce involving micropaleontology will struggle to operate without the availability of these resources [10].

We created an active learning application for micropaleontology, FossilSketch [14][15][16][17][18]. The application provides a teaching environment by providing students with various learning activities [14][15][16]. These learning activities include educational videos, exercises, and mini-games. These activities are designed to help students learn micropaleontology without specialized equipment such as microscopes and real microfossil samples [14][15][16]. These activities are designed using high-resolution images of microfossil embeds sketching and provide automatic feedback [14][15][16] to the students. The application allows the instructor to use existing resources for teaching microfossils without an additional cost to acquire resources [14][15][16]. Since it provides an active learning environment and automatic feedback, students gain specialized micropaleontology knowledge by applying at their own pace while not adding more work required for the instructors [15].

Besides many known advantages of FossilSketch for undergraduate students [14][15][16][17][18], an unexplored area of FossilSketch is its effectiveness on high-school students. Although FossilSketch was developed for undergraduate students and their instructors, this paper argues that this application can be an effective tool for high school students interested in learning about microfossils. Allowing high school students to learn such topics would help reduce the knowledge gap when pursuing higher education [19][20]. In addition, introducing undergraduate concepts to high school students would also inspire them towards STEM (Science, Technology, Engineering, and Mathematics) or specialized fields such as geoscience [21]. Also, it is important to consider how high school students perceive the benefits and consider learning about micropaleontology later in life or college.

Considering that FossilSketch may influence high school students' knowledge and aspiration in geoscience, in this study, we introduced the application during an outreach program – SeaCamp 2024. We focused on exploring the effectiveness of FossilSketch through students' learning outcomes and their sentiments. More specifically, we answered the research question: What aspects of students' learning outcomes from FossilSketch activities shaped their sentiments toward studying micropaleontology?

Literature Review

Self-regulated learning and FossilSketch

The premise of FossilSketch is guided by self-regulated learning theory [22][23]. Self-regulated learning posits that students can rely on themselves to gain knowledge and use effective strategies to learn and monitor their progress [24]. Students self-regulate their progress by setting academic goals and monitoring their progress toward achieving them [24]. Prior studies found that self-regulated learning improves students' academic performance [25] and motivation to learn [26]. Notably, self-regulated learning has been effective in online learning platforms [27], especially in environments that promote active learning approaches [28].

Promoting students' self-regulation while teaching micropaleontology is challenging. Most of these challenges emerge from the need for specialized resources such as microscopes, fossil specimens, and expert instructors to illustrate microfossil variability [8][9][29]. Additionally, a shortage of micropaleontologists [11][12], high equipment costs [13], and lack of time [30][31] to provide activities and immediate feedback to students make it challenging to establish active learning environments [32]. To address the issue of resources while implementing self-regulated learning, researchers focused on utilizing technology to help teach micropaleontology [33]. For example, an e-learning introductory geology course was developed to teach students geology concepts through video lectures, discussion boards, and automated feedback to submitted assessments [34]. The e-learning tool was developed due to computer-based instructions possibly improving students' cognitive engagement and perception of the subject being taught [35] while providing self-regulated learning [36][37]. The authors found that the e-learning course improved students' performance on assessments measuring their geology knowledge [34]. Students who used the e-learning tool also had positive perceptions of the immediate feedback they received [34]. In another example, the authors discussed developing and using a virtual microscope for geology labs. The virtual microscope, which can be used online on a computer, simulates a real microscope by allowing students to interact with 3D samples via zoom controls, adjusting lighting, and providing feedback [35]. Students who used the virtual microscope found the immediate feedback useful and gained confidence in their learning materials through the virtual tool [35]. Both examples indicated that, besides providing students with more flexibility, these tools contributed to students' learning experience [34][35].

Although virtual tools provided good results, researchers also noticed the need for more active learning environments, combining remote, virtual, feedback-driven environments catering to all students' personalized needs [38]. Considering the need, we developed an educational environment called FossilSketch. The application is designed to create a robust learning environment for students and instructors. The application combines virtual power and personalized experience for different students with immediate feedback [15]. In its current form, the application was designed in phases: the pilot and current versions.

Effectiveness of FossilSketch

Prior research found that FossilSketch helps improve geoscience undergraduate students' knowledge retention and motivation to learn more about micropaleontology [16]. Compared to geoscience students who did not use the FossilSketch, undergraduate geology students improved in identifying microfossils and recognizing morphological characteristics [16]. Students who also utilized FossilSketch were more motivated to learn more about micropaleontology than those who did not use the tool [16]. However, more studies are needed to evaluate its effects on learning.

Sentiments and their implications

Prior research on sentiments toward learning indicates that sentiments are an important educational component [29][39][40][41]. Literature supports that positive sentiments towards learning have been associated with improved academic performances [42] and higher engagement when learning [40][41]. Besides an indicator of students' perception, sentiments could reflect students' eagerness and motivation towards learning [29]. For example, Moè and colleagues [29] found that students' attitudes toward learning in school mediate their motivation for academic achievements and positively influence their self-confidence in learning. Similarly, in another study, Schau [39] found that students' positive sentiments toward learning statistics influence their likelihood of attaining high academic achievements. Students with positive sentiments have high self-confidence in learning statistics and less anxiety about the subject than students without positive attitudes [39]. Considering the importance of sentiments in education, exploring how students' learning outcomes from FossilSketch's activities affect their sentiments toward learning more about micropaleontology.

FossilSketch Design

The current version of the application allows students to interact with FossilSketch's activities through the student dashboard. The student dashboard provides access to 10 modules designed around various topics of micropaleontology. Students can track their progress for every activity.

The educational videos offered in the application provide information on various micropaleontology-related topics. Students can first watch educational videos that cover different reasons scientists study micropaleontology and in-depth information on foraminifera morphotypes. Students can then play interactive mini-games to strengthen the knowledge gained from the videos. Afterward, students can complete exercises that use step-by-step procedures to teach complex micropaleontology topics. After completing each activity, FossilSketch automatically provides feedback to students, which they can use to improve their knowledge of micropaleontology. Students' activity scores are calculated using a 3-star system, where 0 stars indicate the lowest score while 3 stars indicate the highest score. FossilSketch's activities use scaffolding and are structured in that students begin learning through videos and continue to build and reinforce their knowledge through games and exercises that become increasingly more difficult with progression.

Research Design and Methods

This study follows a quantitative approach, specifically a correlational research design, and explores the relationship between students' engagement with learning activities and their sentiments toward learning micropaleontology.

Site and Participants

The specific features of FossilSketch were introduced to participants of SeaCamp 2024. Twenty-three students gave their consent to participate in the study. The participating students were divided into groups of 2-3 students (8 groups in total). Every group participated in at least one activity from the available activities in FossilSketch.

FossilSketch Features for the Study

The students were introduced to the following 11 activities while using FossilSketch:

1. Alaska Assemblage Mini-Game: Students were tasked to reconstruct the past environment using benthic foraminifera found in the Gulf of Alaska.
2. Foram Assemblage Mini-Game: Students were tasked to reconstruct the past environment using foraminifera genera.
3. Morphotype Assemblage Mini-Game: Students were tasked to reconstruct the past environment using morphotypes.
4. Morphotype Matching Mini-Game: Students learned to identify foraminifera by their shapes (morphotypes). Students dragged and dropped fossil images into the correct classifications in this game.
5. Foram Chamber Mini-Game: Students learned to identify morphotypes through their foraminifera chambers by dragging and dropping fossil images into the correct chamber types.
6. Ostracoda Assemblage Mini-Game: Students were tasked to reconstruct the past environment using Ostracoda.
7. Ostracoda Outline Mini-Game: Students were tasked to match the ostracodas' different types of outline shapes.
8. Ostracoda Orientation Mini-Game: Students were assigned to rotate the Ostracoda until its sides align with the labels on the different parts of the screen.
9. Morphotype Identification Exercise: Students learned to identify morphotypes by sketching features through careful observation.
10. Foraminifera Identification Exercise: Students learned to identify foraminifera by sketching features through careful observation.
11. Ostracoda Identification Exercise: Students learned to identify Ostracoda by sketching features through careful observation.

Notably, groups were asked to participate in three activities. However, some groups of students participated in more than three activities, leading to varying attempted activities per group. As none of the groups of students participated in the Alaska Assemblage Mini-Game and the Foram Assemblage Mini-Game, the two mini-games were filtered out of the data set.

Measures

In this study, we collected two types of data: 1) student outcomes (scores) and 2) survey data on their perspective toward learning more about micropaleontology.

For outcomes, the data was collected on two aspects: 1) average score and 2) number of attempts. A score for an exercise or mini-game was recorded with a 3-star system, where 1 indicates the lowest score possible, and 3 indicates the highest score possible. The average score describes the group's mean score across all attempts per activity. The number of attempts indicates how many attempts a group made per activity.

For perspective, a survey comprised of four open-ended questions was administered after students had used the application. In this study, we used students' responses to one open-ended question. The open-ended question was: Would you like to learn more about the concepts of micropaleontology? If yes, why? If not, why not?

Procedure and Analysis

To prepare the data for analysis, we first identified the sentiment value for student responses to the survey question. We calculated the students' sentiments score using the Valence Aware Dictionary and sEntiment Reasoner (VADER) [43]. VADER is an analysis tool that measures the sentiments shown in a given input text [43]. The sentiments are measured on a scale from -1 to 1, where -1 means negative, 0 means neutral, and 1 means positive sentiment. Second, based on students' total number of attempts they made in each activity and their score in each activity, we calculated the following variables:

1) Total Score Accumulated – This value represents the students' aggregate score from all their attempts for all activities in FossilSketch.
2) Total Count of Attempts for All Activities – This value represents the aggregate number of attempts students made for all activities in FossilSketch.
3) Total Average Score per Attempt of Activity – This value represents the students' average score per attempt for all activities. This value is calculated by dividing the Total Score Accumulated by the Total Count of Attempts for all Activities.

Due to the small sample size, we used a non-parametric analysis to observe the data. We first conducted Spearman's rank correlation [44] and identified the relationship between students' outcomes and sentiments. Additionally, we used the regression model of the Extreme Gradient Boosting (XGBoost) module to identify what aspects of students' outcomes influenced their sentiments toward learning about micropaleontology. XGBoost is a machine learning (ML) algorithm based on gradient boosting utilizing efficient sequential tree-building algorithms [45]. We primarily utilized the XGBoost algorithm for its feature importance aspect, which describes how much each attribute contributed to the XGBoost model's prediction [46]. To build the XGBoost regression model, we first split the data set into training and testing data sets by utilizing the scikit-learn module (version 1.3.0) to shuffle the data before splitting it into training data and test data. 80% of the shuffled original data set was used as training data, while 20% was used as test data. We used Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score to evaluate the performance of our ML Model. MAE [47], MSE [48], and R^2 [49] are used to evaluate the performance of regression models. MAE measures the absolute differences between predicted and actual values [47]. In the context of our study, this value must be close to 0 and far from 1 to signify high performance, according to MAE. MSE measures the average squared differences between predicted and actual values [48]. This value also must be close to 0 and far from 1 to signify high performance. R^2 Score measures the proportion of variance in the target variable [49]. This value must be positive to signify the high performance of the model.

Results

We conducted a Spearman's rank correlation between students' average score, the number of attempts of every activity, and their sentiments toward learning more about micropaleontology. Table 1 presents the results of the Spearman's rank correlation.

Table I. Spearman correlation between students' outcomes and sentiments

Attribute	**Correlation with students' sentiments**	**p-value N = 8**
Morphotype Identification Average Score	-0.108	0.798
Morphotype Identification Attempt Count	-0.422	0.298

Foraminifera Identification Average Score	0.083	0.845
Foraminifera Identification Attempt Count	0.083	0.845
Ostracoda Identification Average Score	0.455	0.258
Ostracoda Identification Attempt Count	0.455	0.258
Foram Chamber Mini-Game Average Score	0.406	0.319
Foram Chamber Mini-Game Attempt Count	0.678	0.065
Morphotype Assemblage Mini-Game Average Score	0.083	0.845
Morphotype Assemblage Mini-Game Attempt Count	0.083	0.845
Morphotype Matching Mini-Game Average Score	0.116	0.785
Morphotype Matching Mini-Game Attempt Count	0.918	0.001*
Ostracod Assemblage Mini-Game Average Score	0.083	0.845
Ostracod Assemblage Mini-Game Attempt Count	0.083	0.845
Ostracod Orientation Mini-Game Average Score	0.576	0.041*
Ostracod Orientation Mini-Game Attempt Count	0.726	0.103
Ostracod Outline Mini-Game Average Score	0.617	0.035*
Ostracod Outline Mini-Game Attempt Count	0.741	0.283
Total Count of Attempts for all Activities	0.434	0.283
Total Score Accumulated	0.192	0.649
Total Average Score per Attempt of Activity	-0.395	0.333

*$p<0.05$ indicates the significant results

The results indicate that students' sentiments toward learning about micropaleontology are significantly related to Morphotype Matching Mini-Game Attempt Count (p = 0.001), Ostracod Orientation Mini-Game Average Score (p = 0.041), and Ostracod Outline Mini-Game Average Score (p = 0.035).

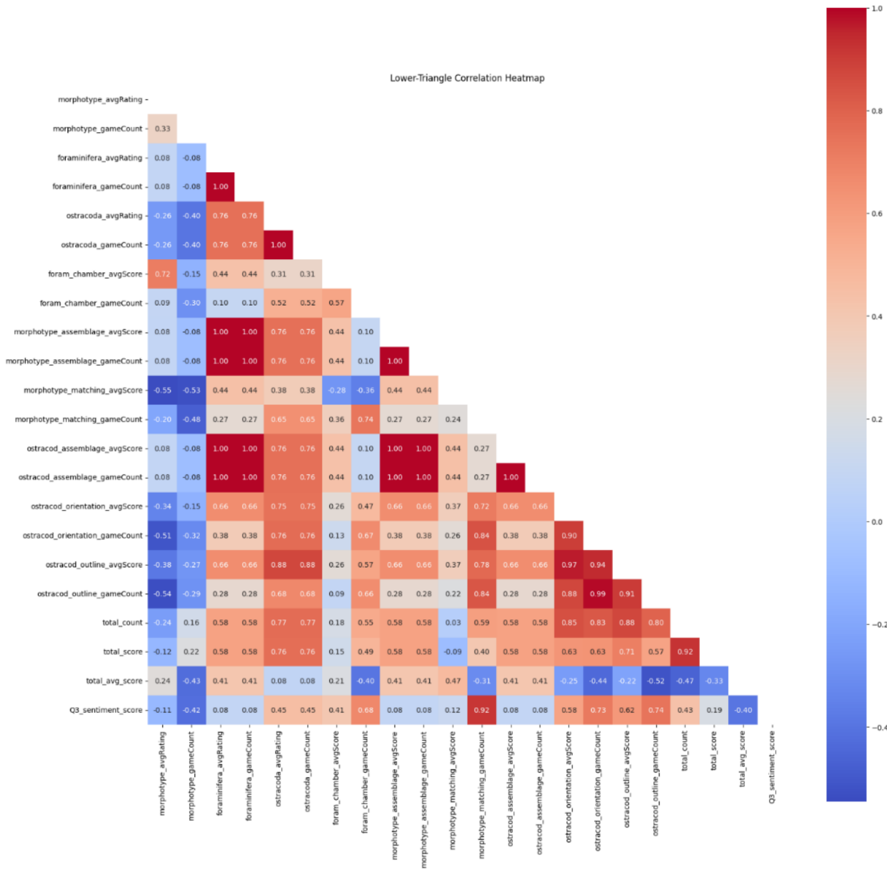

Figure 1. Spearman correlation between student outcomes and their sentiments

Furthermore, we calculated Spearman's rank correlations between all variables. The results are presented in Figure 1. The correlation values between performance metrics for every activity and the sentiment value show an interesting relationship. Generally, correlation values for the number of attempts (game count) are either equal to or higher than the correlation values for the average score. A high correlation for the number of attempts means that the higher the number, the more likely students will have a positive sentiment toward learning more about micropaleontology. The only exception to this was the Morphotype Identification activity, where the correlation score for the average score was higher than the number of attempts.

Additionally, we used XGBoost's regression model to examine the relationship between students' outcomes and sentiments. The results (refer to Table 2) indicate the low fit of the XGBoost regression model. One explanation for this result could be a small sample size (n = 8) and a non-normal data set, which partly has been caused by some activities having more participants than other activities.

Table II. Xgboost regression model for the relationship between outcomes and sentiments

Performance Metrics	**Metric Values**
Mean Absolute Error (MAE)	0.5
Mean Squared Error (MSE)	0.46
R^2 Score	-1975.76

From the results of the feature importance (refer to Table 3), we found that the Total Average Score per Attempt of Activity had a significantly higher value in feature importance than other attributes. These results indicate that the model utilized the Total Average Score per Attempt of Activity to predict the students' sentiments toward learning micropaleontology more. Table 3 lists all attributes with non-zero importance values.

Table III. Xgboost regression model features importance for the relationship between outcomes and sentiments

Attributes	Feature Importance Values
Total Average Score per Attempt of Activity	0.810
Morphotype Identification Average Score	0.174
Foram Chamber Average Score	0.009
Morphotype Identification Game Count	0.008
Total Score Accumulated	0.000

Discussion and Conclusion

This study focused on introducing FossilSketch to high school students during SeaCamp 2024. In this outreach effort, students used the application and were introduced to various mini-games and exercises of FossilSketch, covering an outreach effort to high school students. These activities allow the students to learn about morphotypes. Using the data on students' outcomes and their perceptions toward learning more about micropaleontology, the paper examined the relationship between students' outcomes and their sentiments.

The study's results provide interesting insights into how students' learning outcomes affected their sentiments toward learning more about micropaleontology. The results of the Spearman correlation approach indicated that the Ostracod Outline Mini-Game Average Score, Ostracod Orientation Mini-Game Count, and Morphotype Matching Mini-Game Average Count attributes were significantly correlated with students' sentiments. When viewing from a correlational perspective, we found that generally, the number of times activities were played had more correlation with sentiments than the average score achieved. For instance, for the morphotype identification exercise and the foram chamber mini-game, the number of times played correlated more with sentiments than the average score. In addition, the total number of attempts for all activities had a greater positive correlation with the sentiment than the total average score per attempt for all activities' negative correlation. These results suggest that interaction with the activities themselves has a greater impact on students' willingness to learn than merely achieving high scores in the activities. This finding aligns with existing studies on active learning approaches that indicate that more hands-on experience, or interactive work, generates positive engagement and sentiments towards learning [50][51][52].

While the ML regression model underperformed, its feature importance values shed light on the relationship between students' sentiments and their outcomes. Interestingly, one attribute achieved a vastly higher importance value, which is close to 1 (highly important), compared to other values, which are close to 0 (non-important). The Total Average Score per Attempt of an Activity had the highest importance value, signifying its importance over other attributes. However, Spearman's rank correlation analysis found that the Total Average Score per Attempt of an Activity negatively correlates with sentiment toward learning micropaleontology. These results indicate that students who consistently achieve high scores in activities too easily will be less likely to gain positive sentiment toward learning micropaleontology. The high importance and negative correlation align with previous studies that indicate activities must be matched with students' desirable difficulty to engage them properly [53][54][55][56]. According to studies, students learn more effectively by having more difficulty in the activities they participate in [53][54][55][56]. Conversely, activities' difficulty being too easy leads to students becoming disengaged from the subject [55][56][57][58]. The results of this study may also show a similar phenomenon; the students' number of attempts at activities has a stronger positive correlation. Meanwhile, students' overall score per attempt for the activities has a negative correlation while having high importance in the ML regression model.

In this study, we found that students playing activities on FossilSketch many times and not achieving high scores per activity attempt had more positive sentiments towards learning about micropaleontology. This result may indicate that students prefer more challenging activities to easy activities, where they would achieve a high score while making fewer attempts per activity.

We must consider this factor when continuing the development of FossilSketch. Adding more challenging exercises to the educational tool may help improve sentiments toward learning more about micropaleontology. However, we must not sacrifice the element of interactivity when adding challenging exercises. We must also avoid increasing the difficulty of the activities too drastically, as studies indicate that students become less engaged with activities that they find too difficult [57][58].

The results of this study must be viewed with several limitations. First, the study had a small sample size (N=8 teams). Future studies can be designed with a larger sample size. Second, in this study, we only relied on student outcomes using their score in the 3-star system and did not consider other measures, such as performance in conceptual assessment [16]. Future studies can consider other measures of students' learning outcomes. Third, this study focused on group data, and individual perceptions may vary. Future studies can consider students' individualized learning outcomes. Fourth, not all groups participated in each activity due to the limited time. Fifth, the data is limited to high school students. Future studies can be considered to ensure the same participation requirement for each group or student for FossilSketch. Fifth, we only measured students' sentiments from their perceptions in this study. Other data modes and affective domains may also be considered in the future for a better understanding of student outcomes. Also, future studies can consider other overt behaviors of students when using FossilSketch using multiple data modes such as observation [59] and instructor perspectives of students' learning.

From the results of this study, we also surmise multiple implications. First, the study opens the door for using online active learning teaching applications for high school students. This study provides a basis for the idea that interactive activities promote positive sentiments. Also, the study emphasizes the importance of tools that could promote self-regulated learning in students. Due to the incrementing stages of informational videos, mini-games, and exercises, students could monitor their progress and adjust their pace. We argue that future online learning platforms with more interactive activities will likely result in positive sentiments, attitudes, and motivation towards the subject they are learning. We also emphasize that in any application, the design and structure of the material play a significant role. We suggest that the interactive activities must be balanced on a difficulty level in such applications. As too-easy activities may result in disengaged behaviors, too difficult exercise may result in a decline in learning interest [60].

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