Analysis of Students' Personalized Learning and Engagement within a Cyberlearning System

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Abstract

"Advance Personalized Learning" is one of the 14 grand challenges of engineering as identified by the National Academy of Engineering. One possible approach for this advancement is to deploy systems that allow an investigator to understand the differences in the learning process of individuals. In this context, cyberlearning systems, like remote and virtual labs, that use networked computing and communication technology to reach a large number of learners offer the affordance to uniquely identify learners and track their learning process in real-time. Motivated by this idea, this study aims to investigate personalized learning and engagement within a cyberlearning system, called the Online Watershed Learning System (OWLS) that combines features of both remote and virtual labs. This cyberlearning system utilizes learning resources generated by a real-time high-frequency environmental monitoring system, called the Learning Enhanced Watershed Assessment System (LEWAS).

To understand individualized learning and engagement, the OWLS is advanced with a user-tracking system. Previously, the OWLS used a Google-Analytics based user-tracking system. This new user-tracking system can identify individual users and their actions across devices. A pilot study was carried out by designing an OWLS-based learning task and implementing it within a senior level Environmental Science classroom for exploring personalized learning and engagement within the OWLS. Informed by the engagement theory and the literatures on learning analytics, the study follows a pre-experimental research design where students completed the OWLS-based learning task followed by a post-survey within the in-class time. Results indicate that students' learning scores are significantly related to the time students were spending outside the OWLS for completing the OWLS-based task. Various engagement patterns/ strategies taken by individual students to complete the task were also revealed. The study shows that a custom user-tracking system, like the one developed in this study has the potential to overcome several limitations of the google-analytics based user-tracking system by providing fine-grained individualized student data that can help in understanding students' engagement behaviors within a cyberlearning system. Finally, the study has implications of how a cyberlearning tool, like the OWLS, can be utilized in a hybrid classroom setting for helping students gain environmental monitoring knowledge, and skills in real-time data analysis, leveraging the idea of technology-enhanced laboratory instructions within a classroom environment.

1. Introduction

Advancements in computing and communication technologies have led to the development of powerful technological resources for teaching and learning. The 2017 Nation Education Technology Plan (NETP) of the U.S. Department of Education recommends that for every level of education, institutions should utilize learning technologies to facilitate education anywhere and at any time [1]. Specifically, for the success of American postsecondary students including students from diverse socioeconomic and ethnic backgrounds, genders, age-groups, and learning needs, the supplement of the NETP report includes recommendations for using these technologies to leverage student-centered approaches of teaching and learning [2]. These approaches are beneficial to promote personalized learning experiences by placing an active role on the student and making them the agents of their own learning [3]. The NETP report further recommends that for assessing individual competencies using technology, studies should consider collecting and using real-time learning data for providing targeted assistance to students [2]. Such assessments are known to improve students' learning and promote personalized learning [4]. Advancing personalized learning is one of the 14 Grand Challenges of Engineering promoted by the U.S. National Academy of Engineering [5]. One possible approach for this advancement is to deploy systems that allow an investigator to understand the differences in the learning process of individuals, which can be utilized to create instructions tailored to an individual's need. The focus of this paper is to investigate such personalized learning and engagement within a cyberlearning system developed in the context of environmental monitoring to promote technology-enhanced laboratory instruction.

Cyberlearning systems are an innovative learning technology using networked computing along with communication technology to support teaching and learning [6], [7]. Diverse student population can access its learning resources regardless of their proximity to traditional classroom spaces. It also offers the affordance to develop personalized learning spaces where learners can be uniquely identified and their progress can be digitally traced [8]. Cyberlearning systems, including remote labs, virtual labs, online hybrid labs and augmented reality labs have gained popularity as tools that can engage individual students to gain important engineering skills in problem-solving, modeling and experimentation [9], [10] by substituting or complementing tradition laboratory instruction. For a long time, evaluation of cyberlearning systems for pedagogical effectiveness has been the focus of various empirical studies [9]. In recent years, cyberlearning systems are being equipped with user-tracking capabilities (data acquisition systems), thus enabling to investigate the individualized learning processes. These tracking methods can store/log the digitized traces of individual students, which can be represented by the time sequence of actions, such as mouse clicks, typed keys, and navigation through web-pages [11], [12]. Analysis of the logged student data assists in identifying the preferences and bottlenecks faced by each learner [13]. It can also explain the level of engagement of the students within the cyberlearning platform [14], [15] their study habits [16] and their patterns of inquiry while solving a problem [17]. These in-depth continuous assessments can allow educators to evaluate individual students' performances, provide targeted feedback to students, understand the efficiency of the learning materials, and validate/evaluate the teaching strategies, which can inform the quality of education, and lay the foundation for a more effective technology-infused education system [18]. By reviewing empirical studies in the domain of learning analytics and educational data mining, it appears that research based on student analytics will be a major research topic for the upcoming years [3], [18], [19]. Additionally, by recognizing how personal learning experiences differ within cyberlearning systems, steps can be taken to advance a cyberlearning system to adopt the personal learning style, pace, and interest of diverse student groups.

This study is a part of a project that focuses on advancing the research potential of a cyberlearning system, referred to as Online Watershed Learning System (OWLS) in this paper.

OWLS is an interactive open-ended guided cyberlearning system delivering integrated live and/or historical environmental monitoring data (water quality and quantity, and weather data) from a high-frequency environmental monitoring system, called the Learning Enhanced Watershed Assessment System (LEWAS), to end users regardless of the hardware and software platforms used for environmental monitoring education and research [20], [21]. Until now, the OWLS and the LEWAS have been introduced in 33 courses (freshman to graduate level) across 9 institutions and in 3 countries [22], [23]. To understand individualized learning and engagement, OWLS is advanced with a user-tracking system. First, this paper presents the functionality of the user-tracking system. The paper includes details of an OWLS-based learning task designed and integrated within a senior level classroom for environmental monitoring education. Then the research design and results of a pilot study implemented to assess individual students' engagement and learning within the OWLS while completing the learning task are presented. Finally, the paper demonstrates that a custom user-tracking system, like the one used in this study, has the potential to overcome several limitations of the google-analytics based user-tracking system by providing fine-grained individualized student data that can help in understanding students' engagement behaviors within a cyberlearning system.

The remaining sections of the paper are organized as follows. Section two includes a discussion of the theoretical frameworks that are relevant in the context of this study. In the third section, the OWLS and its user-tracking system are described. The research design employed to implement the OWLS-based learning task including the settings, participants, and data collection method are presented in the fourth section. The fifth section includes the study results and discussion. Finally, the conclusion and opportunities for future work are described in the sixth section.

2. Theoretical Framework

2.1 Engagement theory

The literature on engagement is diverse and each researcher has explained it in various dimensions [24]. For example, Pace's definition includes the idea of students' involvement with his/her academic environment, and Austin's definition includes students' interaction with the learning environment. Both of these notions of engagement related it to behavioral features of a student [24]. According to include name of author here [25], the term engagement encompasses constructs such "as the quality of effort and involvement in productive learning activities" (p. 6). Engagement is also viewed as a "meta" construct that encompasses three aspects of engagement: behavioral, emotional and cognitive [26]. Behavioral engagement builds on the idea of students' participation, effort, attention, positive conduct and persistence with activities within a context. Emotional engagement relates to the positive and negative reaction to do a certain activity. While, cognitive engagement includes the idea of the level of investment, the thoughtfulness, willingness and strategy put forth for a certain task. In this study, engagement will be explored in terms of behavioral engagement within the context of human-computer interaction, where engagement is defined as the human response to computer-mediated interactive systems [27].

For traditional classrooms, behavioral engagement has been measured with class attendance or participation in class [28], [26], which are the only visible indicators of engagement. Similarly, participation in a cyberlearning platform can be observed to measure behavioral engagement [29], [30]. For measuring participation on online platforms time of engagement and the number of clicks have been utilized [31]. Similarly, for this study, these measures will be used to assess the behavioral engagement of the students. However, for a system like the OWLS, the aim is not only to facilitate engaging user experience but for users to behave in certain ways so that they have positive learning outcome utilizing the system [29]. In other words, the goal is not to increase the number of clicks on resources or engagement time within the OWLS, but the purpose is to engage users to invest time and effort in accomplishing a learning task with the system so that they can learn and develop skills utilizing it. The behaviors exhibited by an individual student within and outside the OWLS for accomplishing the learning task can be an indicator of the level of engagement as well as the engagement pattern that leads to learning.

Additionally, engagement is regarded as a multidimensional construct that is *malleable, context-specific and reactive* to the changes in the learning environment [30], [26]. It mediates the impact due to the changes in the learning environment on achievement. This necessitates to clearly unfold the process of engagement and to understand its contribution to the learning of an individual student within a specific context [32], which is the focus of this study.

2.2 Relevant literature on user tracking data

There have been several research studies that have utilized user-tracking data to get insights about students' actions within a learning environment and the way it impacts their learning. From a critical review of these studies, it is known that user-tracking data are usually collected using one of the following ways: 1) learning management system (LMS), 2) custom user-tracking system or 3) Google Analytics-based system [3], [14]. An LMS, for example, Moodle or Blackboard, are used with online or traditional courses that can collect user-tracking data and generates statistical reports to summarize users' activities related to the utilization of course resources [33], [34], [35]. These can track individual users, but the information collected is very basic, such as the time when a quiz was accessed or time when students submitted an assignment or number of times a resource was accessed, and it cannot trace every interaction a student does with the computer for solving a certain learning task/problem to complete an assignment [3]. It provides data to understand students' online participation that often aids the management for improving institutional teaching and learning. On the other hand, Google Analytics-based user tracking systems can track students' actions, such as the time when a cyberlearning system or its certain web pages are visited, number of times visited, average duration of each visit, and whether a site has new or returning visitors [3], [14], [21]. These data are then presented at an aggregate level on the Google Analytics dashboard rather than data at an individual level as it cannot track a student across devices [14]. An aggregate description can mask the precise learning behaviors and strategies that students employ while working on a system. Again, for both these technologies, user-tracking data is stored in a proprietary server and the data analysis is limited by the functionality of such systems. In comparison, developing a custom user-tracking system can benefit researchers in collecting in-depth user-tracking data as well as in tracking individual users across devices, and storing these data in a secure custom-database. This enables researchers to build trust among users about the privacy of their data storage and usage, which can improve users' experiences with a learning technology [36]. A custom user-tracking system can also be tailored for collecting necessary and in-depth data in a required format, and have added functionalities, which can considerably save time in data pre-processing for producing actionable insights. This paper aims to present the functionality of the custom user-tracking system and compare its advantages over a Google-Analytics system for in-depth assessment of individual students' user-tracking data. In the following paragraphs, some studies are reviewed to show how user-tracking data has been utilized for cyberlearning systems.

Within the context of cyberlearning systems, only a few studies have indicated the integration of user-tracking capabilities with their cyberlearning system. Some virtual and remote labs (VRL) are integrated with LMS for collecting user-tracking data [37], [38]. For example, UNILAB, which is a collection of 15 remote and virtual labs on automatic control, was deployed into the Moodle LMS to promote online sharing of the lab resources, and to support the administration, maintenance, interaction between students and teachers, and reporting of various online events [39]. Another study integrated a user tracking system for their remote laboratory to portray the effectiveness of their remote lab [40]. An open remote laboratory, called VISIR has a built-in user tracking system to measure resource utilization by collecting information on access frequency over the semester, access per type of user, average access per task, usage distribution over the semester and users' average access [41]. These data showed a positive correlation between students' grades and VISIR usage. It should be noted that these studies focused on evaluating their VRLs. Thus, the user-tracking data was used to establish the effectiveness of their VRLs and not for explore the relationship student learning and engagement.

Branch & Butterfield [16] have developed a web-based simulation environment with a user tracking system, which tracks students' mouse movement and clicks and keyboard event with corresponding time. Analysis of the user tracking data using ensemble averages of successful and unsuccessful students helped in identifying the variation in their mouse locations along with their study habits and problem-solving strategies, which lead to the modification of educational materials. These data also detected that students attempted to interact with the non-interactive components of the system, which lead to redesigning the system. The analysis of the user tracking data collected within a cyberlearning system, called gStudy, provided information about the frequency, pattern, and duration of actual studying activities of the students [42]. It reflected different ways of students' self- regulated learning over time although every student was trained and exposed to the gStudy before the actual study activity. They demonstrated that transition graphs are also helpful in visualizing the pattern of activities. It is suggested that the frequency of actions can be compared to student performance and motivation or to cluster student groups. However, there is a need for techniques for examining patterns across groups of students. Similar to the earlier study, Kinnebrew, Loretz & Biswas [43] from their classroom study with a cyberlearning system, called Betty Brain with custom user-tracking capabilities, suggest that user tracking data provides an opportunity to accurately understand students' learning behaviors patterns and strategies used, by capture all the interaction of a students within the learning environment [43], [44]. They explored the differential sequential data mining algorithm to identify differentially frequent patterns between high and low performers. Baltierra [14] developed a user-tracking system with login functionality for a web-based healthMpowerment.org (HMP) site and complemented it with Google Analytics data. They engaged 15 participants in a pilot study for one month to measure the usability and efficacy of the HMP system. They also measured the level of engagement within the HMP with time spent (total and across sections) and points earned through various activities performed within the

HMP. They found that there is a significantly high correlation between the total times spent with points earned and site satisfaction for 9 participants who were active throughout the one month period. In addition to the approaches used in the reviewed studies, these studies have been helpful in showing that there is a variation in how each student engage in an online learning environment and its relationship with the learning outcome varies in a different learning context. Thus, it is important to explore individualized engagement and learning within the OWLS, which is developed in the context of environmental monitoring.

3. OWLS and user tracking system

OWLS is an interactive open-ended guided cyberlearning system of the LEWAS, which is a unique real-time high-frequency environmental monitoring system established to promote environmental monitoring education and research [20], [45], [46], [47]. The LEWAS includes the following four stages: 1) environmental monitoring instruments collecting water quality and quantity data as well as weather data, 2) data processing, 3) data storage and 4) end-user interfaces/web applications, which enable users to visualize and use LEWAS data, e.g., the OWLS, for research and education [48], [49]. The LEWAS initiated by providing remote access to real-time environmental data to students [45], [46]. To evaluate its effectiveness in increasing students' motivational gain, expectancy-value theory (i.e., intrinsic, attainment, utility, and cost value) was used [45]. Following this study, the OWLS was developed using HTML5, which is accessible on any device and browser over the internet. Compared to different types of labs, OWLS combines features of both remote and virtual labs. Analogous to remote labs, it remotely situates users to a physical field site location that has various environmental instruments, and let users monitor and analyze the continuous high-frequency environmental data from those instruments. But, unlike remote labs, these instruments are fixed in their setup and cannot be manipulated by users. Similar to virtual labs, OWLS allows users to navigate a simulated environment through geographic depictions of the physical world. The OWLS has several components and features including live camera feed of the monitoring site, an interactive live graph, local weather radar, background information about LEWAS and a local watershed, and several case studies to learn about the environmental changes at a local watershed, monitored by LEWAS. Users also have the ability to download data for comparing, contrasting and analyzing the environmental data. Classroom testing of the OWLS led to the evaluation of the effectiveness of the OWLS in increasing students' learning and motivation in environmental monitoring concepts [20], [21], [49], [50]. Additionally, Google Analytics based user-tracking system was integrated into the OWLS, which was able to detect groups of users accessing the OWLS components from around the world [51]. However, it was not able to identify individual users across devices and was not able to detect users' actions within an OWLS webpage. A user-tracking system was developed within the OWLS to address the limitation of the Google Analytics based user-tracking system and to understand in-depth students' strategies in solving an OWLS-based learning task. This initiative is for advancing the research potential of the OWLS in the context of personalized learning.

A user-tracking system is developed for the OWLS following the client-server architecture. It includes a login system to identify individual users and tracking functionalities for detecting each user's interaction within the OWLS. To fully capture users' actions on the OWLS browser, the tracking system collects both the process of interaction (e.g., dropdown clicks, playing videos, etc.) and its product (e.g., the name of the environmental parameter chosen, dates chosen, etc.) information, unlike many other user tracking systems [52]. A database is used to securely store all users' login and user-tracking information. This makes the OWLS a secure learning environment for the users and addresses the concern of protecting sensitive personal data within a cyberlearning system [52]. The functionalities of the user-tracking system are as follows: a) authorizing and authenticating a user to uniquely identify a user across the OWLS webpages and various devices, such as desktops, laptops, and tablets, b) retrieving each of the web pages accessed by an user to solve a problem, c) retrieving user's action information within a webpage to detect the various objects, such as YouTube videos, buttons, and parameter from drop-down menus clicked by the user, d) retrieving information useful to detect the various devices used by an user and to identify the compatibility of the user- tracking system with various operating systems, browsers and device types/models, e) retrieving users' location information to identify from which part of the world a user is accessing the system, and f) retrieving users' browser status at a regular interval of time (60 sec) to detect whether a user is actively using the OWLS browser or using a different browser or have gone offline. This last feature overcomes the limitation of logging out users after a fixed interval of time in the middle of their interaction commonly implemented in studies for effective estimation of engagement time [14].

4. Research method

An IRB approved pilot study was carried out to implement the OWLS for investigating personalized students' learning and behavioral engagement. The research question is:
How individual students learn and engage with a cyberlearning system (i.e., OWLS) to complete an environmental monitoring task?

A senior-level course "Monitoring and Analysis of the Environment" at a large university in the eastern part of the United States was chosen. This course offers a complete hands-on-laboratory- and field-based experience and information on the principles and methods for field monitoring and sampling. For this study, an OWLS-based environmental monitoring task (hereafter referred to as a OWLS-based task) and an online post-survey were developed in consultation with the instructor. The specific learning objectives (LO) of the OWLS-based task were to: 1) determine the importance of continuous environmental monitoring data, and 2) analyze, compare, contrast and interpret real-world environmental monitoring data. These objectives were consistent with the course learning objectives. For the OWLS-based task (see details in Appendix A), students had to answer questions related to the following three themes: a) description of the OWLS targeted watershed and its current water quality condition, b) benefits of continuous environmental monitoring data, and c) analysis of a specific conductivity event that was available to students as a case study at the LEWAS field site. The course had two section, but data were collected from one section with 16 students. It was designed as an in-class task that required students to explore various components of the OWLS and complete an electronically written report based on their findings. It provided a means for measuring individual students' learning utilizing the OWLS. An online post-survey was used to collected students' background information, their perceptions towards learning with the OWLS and their perceptions towards learning values of various components of the OWLS. One student couldn't participate due to computer-related issues which lowered the sample size to 15. The research design followed a pre-experimental design [53] as shown in Table 1 where students completed the environmental monitoring task using the OWLS and then completed the post-survey. As the students worked on the OWLS, their interactions were tracked by the user-tracking system and stored in the database.

Table 1. Pre-experimental Research Design

Student Population	**Self-Selection Sample (ENSC 4414)**	**Treatment**	**User Tracking data**	**Post-Survey**
Students from a course meeting LO1 and LO2	n=15	Students were familiar with the OWLS as they previously used it for a different assignment. Students were asked to complete the environmental monitoring task in-class. No further demo of the OWLS was given.	Data collected using the user-tracking system of the OWLS	Data Collected using a survey

5. Results and discussion

5.1 Students' background information

Of the15 participants (7 males and 8 females), majority of them (11/15) had taken or were taking a senior level lecture-based course on water quality. According to students' self-assessment, they had different levels of proficiency in water quality concepts: 7 students were "advanced", 7 students were "intermediate" and 1 student was "basic". Additionally, this course had already used the OWLS without the tracking system for a prior assignment in the course, which helped the students to have familiarity with the system. The differences among students with respect to their gender, background knowledge, and proficiency level was not investigated in this study because of the small sample size (n=15).

5.2 Behavioral engagement measurements

To measure individual student's level of engagement within the OWLS, the data collected by the user-tracking system in the database was analyzed. The following parameters were calculated for analysis: total time on task, total Off OWLS time, total On OWLS time, and total number of clicks within the OWLS. The total time on task was calculated by taking the time difference between a student's first visit to the OWLS home page and the time the student logged out. This time measurement can be assumed to be the total time a student had spent on the OWLS-based task. It should be noted that students were not restricted to only work on the OWLS-based task during this time. However, the instructor and the researcher observed that the students were either on the OWLS browser or on the electronic report during the in-class time. The total Off OWLS time was calculated by summing all the time periods when the database registered that a student is not using the OWLS browser. A student might not use the OWLS browser if he/she is working on the electronic report or doing calculations on the excel data sheet downloaded from the OWLS or busy with other activities on the computer. Making the assumption that the student was Off OWLS between consecutive “Off OWLS Time” measurements, the Off OWLS time was calculated with a maximum error of ±60 seconds for each Off OWLS time period. The time calculation is demonstrated in Figure 1. The Off OWLS time was subtracted from the total time on task to find the On OWLS time, which is the time a student was actively using the OWLS browser. The total number of clicks is the sum of all the clicks within the OWLS. The total On OWLS time and the total number of clicks can be considered as a measurable variable for the level of engagement within the OWLS, the Off OWLS time can be considered as the level of engagement with the work outside the System 1 to complete OWLS-based task, and the total time on task can be considered as the measure of engagement with the complete OWLS-based task. Figure 2a shows all these measurements for each of the 15 students. To complete the full task in-class, these students spent in a range of 29 to 59 minutes with an average of 42.41 minutes. Within this time, students were On OWLS for around 6 to 20 minutes with an average of 13.44 minutes. They were Off OWLS for times ranging from 9 to 49 minutes with an average value of around 29 minutes. This shows that the students were on the OWLS for less amount of time compared to the time they were out of the OWLS. The total number of clicks within the OWLS ranged from 10 to 44 clicks with an average of 29 clicks. Using Spearman correlation it is found that the total On OWLS time and the total number of clicks have a significant and positive correlation ($\rho = 0.9$) at 0.01 level of significance (Figure 2b), suggesting that either of it can be considered as a measure for the level of engagement within the OWLS.

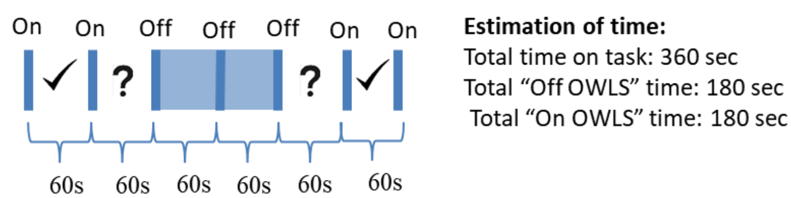

Figure 1. Calculation of the “On OWLS” and “Off OWLS” time with one “Off OWLS” time period

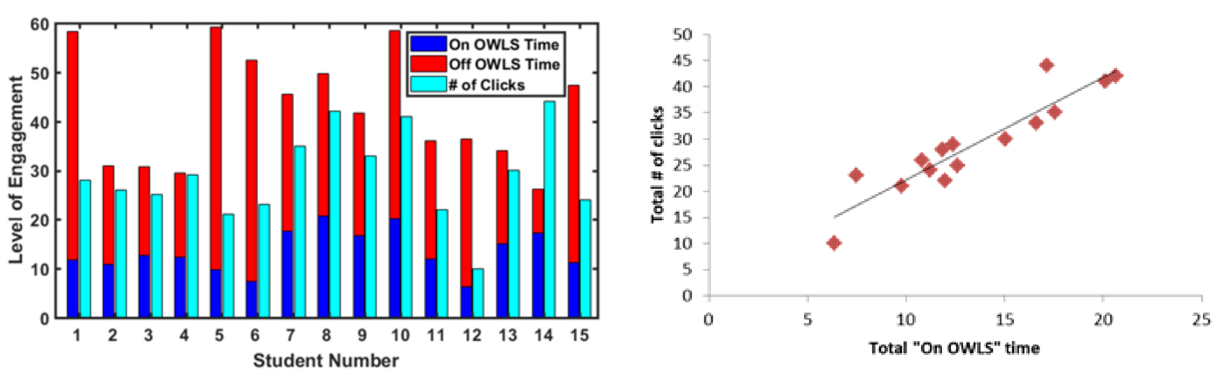

Figure 2. (a) Each student’s “On OWLS” time, “Off OWLS” time and total number of clicks (left); (b) Shows the correlation between students’ “On OWLS” time and total number of clicks (right)

5.3 Level of engagement and learning outcome

To measure students' conceptual learning, a rubric was iteratively developed in consultation with the instructor to score the OWLS-based task (Appendix B). The first draft of the rubric was created by looking into the assignment requirements. Next, it was used to grade some of the randomly picked assignments, which helped in improving the rubric according to students' responses. Figure 3 shows the grades of the 15 students out of a maximum score of 21. The grades ranged from 7 to 18, with a mean of 12.2 and std. dev. equals to 3.825; indicating that the scores were moderate and widely spread out.

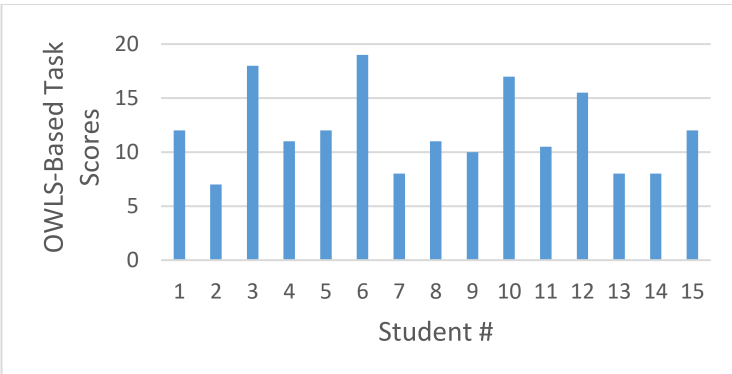

Figure 3. Conceptual learning scores for the 15 students on the OWLS-based task

From literature, it is known that the relationship between level of engagement and learning outcome varies in different educational context [27]. In the context of System 1, there is no prior research that investigated this relationship (i.e., between learning and engagement). Thus, the focus of this study is to explore if there is a relationship between any of the four level of engagement, and learning. This led to finding the correlation between the four different measures of level of engagement with learning. Specifically, Spearman's correlations were computed between the scores on the OWLS-based task and the following measures of level of engagement for 15 students: total On OWLS time, total number of clicks within OWLS, total time on task and total Off OWLS time (Table 2). The total On OWLS time had a low negative correlation (ρ= -0.31) with the scores. Similar relationship was found out between total number of clicks and scores (ρ= -0.42). This consistency in result is due to the significant correlation found between the On OWLS times and total number of clicks. For total time on task and scores, there was a low positive correlation with Spearman coefficient (ρ) equal to 0.49. In comparison, the correlation was significantly positive at the 0.05 level of significance between the total Off OWLS time and the scores. From these four results it can be interpreted that in the context of the System 1, there is a positive relationship between students' level of engagement with the work outside the System 1 to complete OWLS-based task, and learning. This might be true as OWLS is a cyberlearning tool that allows students to explore and monitor the environment of the OWLS-targeted watershed and to download the data. But, students need to put in significant amount of time outside the OWLS to analyze the downloaded data, evaluate environmental events and report the finding in the electronic report. Therefore, students had to spend a substantial amount of time outside the OWLS for performing better on the OWLS-based task. This trend is being further studied with a larger sample size, which is not presented in this paper.

Table2. Comparison between measures of engagement and learning scores

Different measures for Level of Engagement	**Learning Scores**			
	N	**Spearman ρ**	**p-value**	**Level of significance**
Total On OWLS time	15	-0.31	0.2554	Non-significant
Total number of clicks	15	-0.42	0.1183	Non-significant
Total time on task	15	0.49	0.0633	Non-significant
Total Off OWLS time	15	0.56	0.0291	*0.05* level of significance

5.4 Engagement patterns

Figure 4 shows the navigational pattern of each student within the OWLS, differentiating On OWLS and Off OWLS time periods, for the specific environmental monitoring task. For each student's path, the full height lines represent the On OWLS times and the small height lines show the Off OWLS times, while each color represents the different webpages visited by the students within the OWLS during the total in-class time (75 min). From this graph, various student engagement behaviors can be interpreted visually. First, it can be seen that the most commonly used pages were the live graph, data download, watershed summary, and the case study pages. Second, some students also went to live camera, LEWAS intro, key components, photos, glossary, map, site map, radar, and other pages. Third, student #12 and #15 seemed to use multiple browsers while accessing the OWLS. Student #12 opened live graph in one browser and LEWAS intro in another, while student #15, first opened two browsers, then opened four browsers, which can be detected by the alternating colors in the graph. Fourth, most of the users closed their browser/s after completing the task, but students #7 and #8 kept their browsers open even after their class. Moreover, student #7 seemed to go back and forth for using the OWLS browser between 3.30 and 3.40 pm. Fifth, there seems to be a frequent activity trend in which students were accessing the system for the OWLS-based task. Students were mostly navigating from the home page (grey color) to the watershed summary (dull green), to the live graph (maroon), to the case studies (light blue), and finally to the data download page (bright download page (bright green). These types of information were helpful in understanding individual student’s behavioral engagement pattern within the OWLS- providing data on students’ strategies in solving the problem.

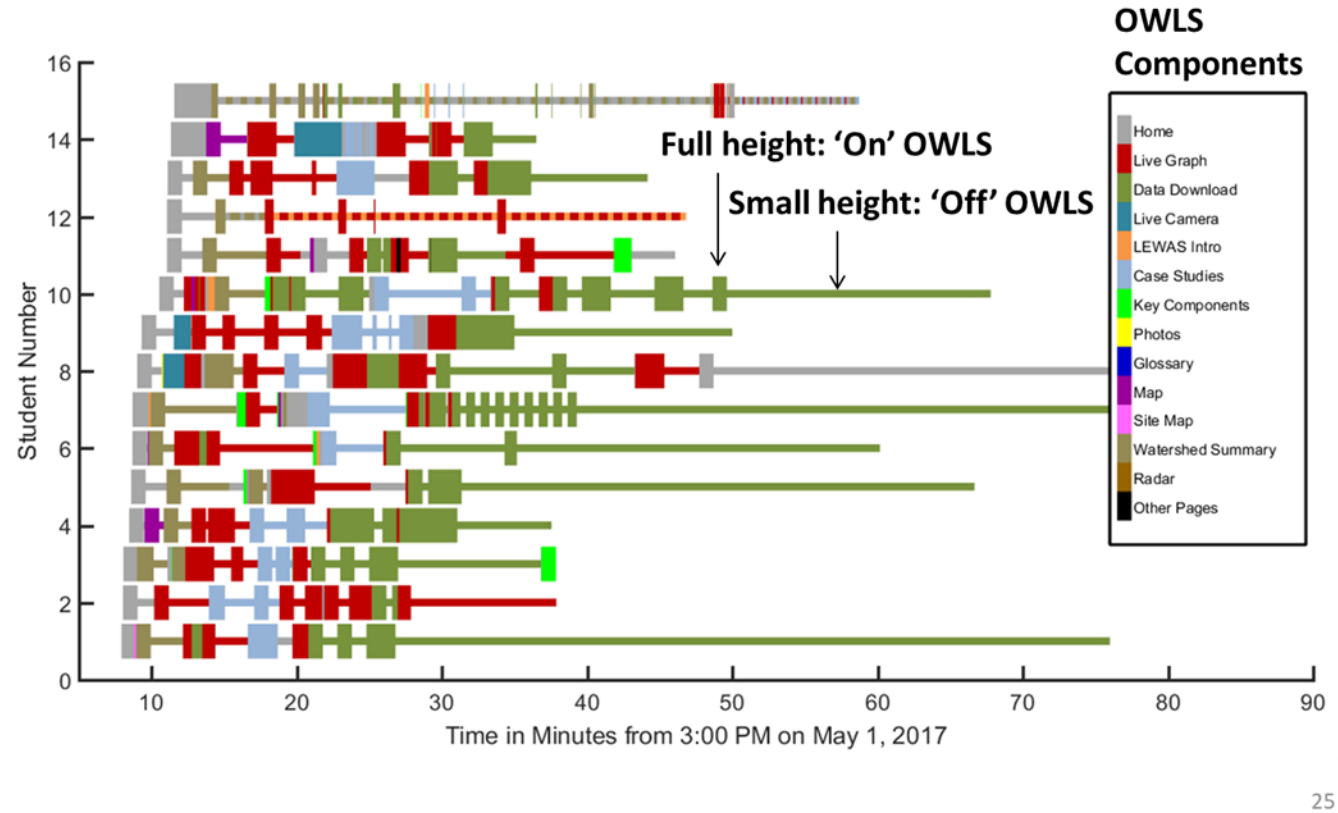

Figure 4. Each student’s “On OWLS Time”, “Off OWLS Time” and total number of clicks

5.4 Resource utilization

The user-tracking data also provided information to understand the variability of the utilization of the OWLS resources by the students for the specific environmental monitoring task. Figure 5 shows a bubble plot to represent the number of times each of the OWLS web pages has been accessed by each student. The sizes of the circles are proportional to the usage of each of the OWLS components by each of the students. If a OWLS component is used n number of times, the radius of the circle is calculated as $r = \log(n+1)/0.2$, where 0.2 is a constant determined by trial and error with the plot as in [56]. It is seen that the singleGraph (or live graph) page and the rawData (or data download) page was the most frequently utilized page followed by the case study pages and the index (or home) page and watershed summary page. The pages, such as components of the LEWAS, LEWAS introduction and overhead view (or map) were moderately used. The other pages were very less used. Comparing this usage with the OWLS-based task, it can be said that the usage of the OWLS resources was related to the assignment structure as the most used pages were the ones that were the “must use” pages of the OWLS for the particular task. This result also corresponds with the results shown in Figure 4.

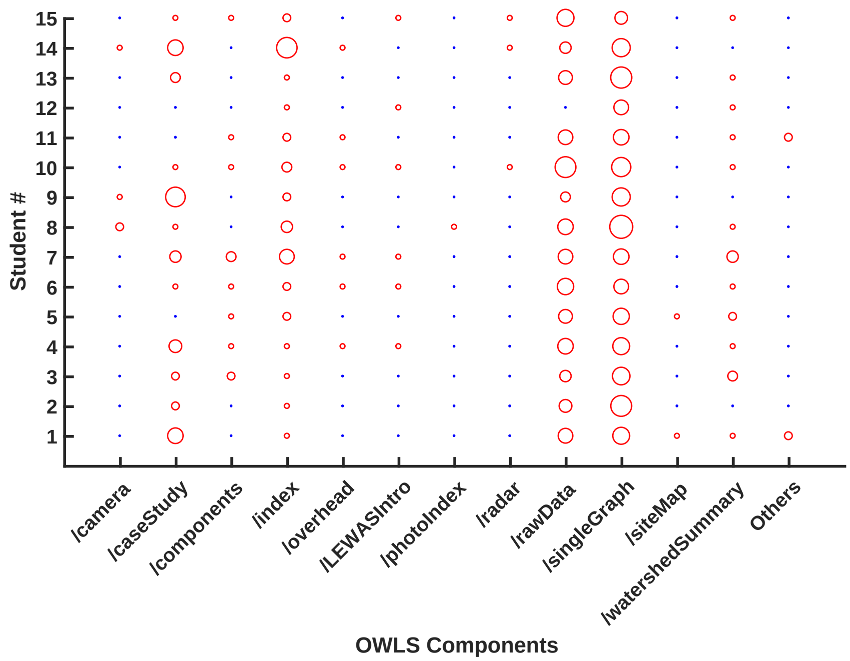

Figure 5. Total number of clicks on each of the OWLS webpages clicked by each of the students

5.5 Efficiency of the user-tracking system

In this section, the efficiency of the newly developed user-tracing system in comparison to the Google-Analytics-based user-tracking system utilized earlier with OWLS is presented [51]. First, the pilot study results show that the developed user-tracking system is able to track each student's engagement within the OWLS across devices, like laptops, desktops, etc., which was one of the limitations of the Google Analytics-based user tracking system [51]. Additionally, the new user-tracking system also detected the operating system, device type and the browser information of each student's computer, which was used to access the OWLS. This provided evidence that the new user-tracking system is compatible with several browser types, operating systems, and device types without installation of any additional software.

Second, this user-tracking system has the potential to detect each student's specific actions within a webpage, which was not possible with the previous Google Analytics-based system. Figure 6 provides an example of the sequence of actions derived from the user-tracking data collected by the user-tracking system of the OWLS of a student, who completed a similar OWLS-based environmental monitoring task like the one used for this pilot study. The figure demonstrates the exact sequence of OWLS components/web pages chosen (in red) by the student and the action employed within each of the web pages (in blue) to complete a similar environmental monitoring task. It also shows the time when students went off the OWLS and when they come back to work on the OWLS. The data also captures the student's login and logout time from the OWLS. This clearly portrays that the user-tracking system has advanced the research potential of the OWLS in the context of personalized learning. This type of user-tracking system is beneficial for any future research agenda related to understanding individual students' learning behavior within a cyberlearning platform.

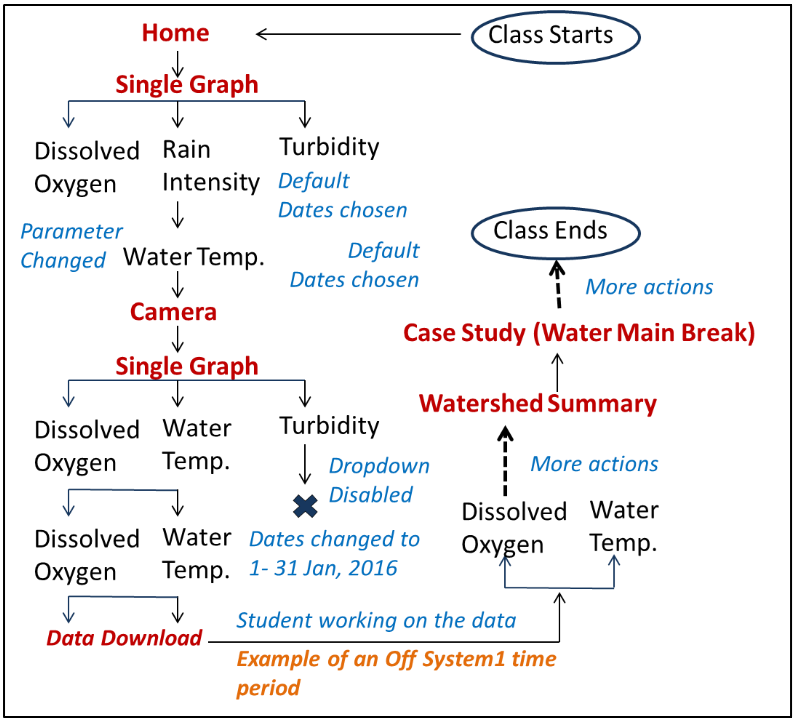

Figure. 6. An example of sequence of actions derived from the user-tracking system of a student completing an OWLS-based environmental monitoring task.

To compare it further with the Google Analytics-based system, calculations were done with the current data to find out the total On OWLS time that would have been produced by the Google Analytics-based system if it could be used for measuring the individual engagement of the students involved in the pilot study. It is to be noted that Google Analytics records only the timestamp when a web page is visited and does record the time he/she left the webpage. As shown in Figure 7, the Google Analytics-based total On OWLS time (light blue bars) was compared with the total On OWLS time (dark-blue bar) and Off OWLS time (yellow) calculated by the new user-tracking system. It can be observed that for all the students, Google Analytics system over-estimated the total On OWLS time compared to the new user-tracking system, providing evidence for the effectiveness of the new user-tracking system. From this result, it can be said that in the context of the OWLS, this study is able to show better measurement of engagement time than done before.

Moreover, the new user-tracking system provides data to estimate when students were using the OWLS and not using it. It also provides information to know when a user logs out or becomes offline from the OWLS, while the Google Analytics-based system was able to find only the time when the last page was accessed by an user and not when they left that page.

From literature, it is known that Google Analytics is an easy tool that is often integrated into online learning technologies for capturing students' actions [3], [14]. However, this study provides evidence to demonstrate that custom user-tracking system, like the one developed for this study, is a better choice for tracking individual students' interaction within a cyberlearning system compared to a Google Analytics-based user-tracking system. Moreover, it facilitates the measurement of engagement time on an online environment, which has been regarded as a variable that is difficult to measure even utilizing LMSs [31].

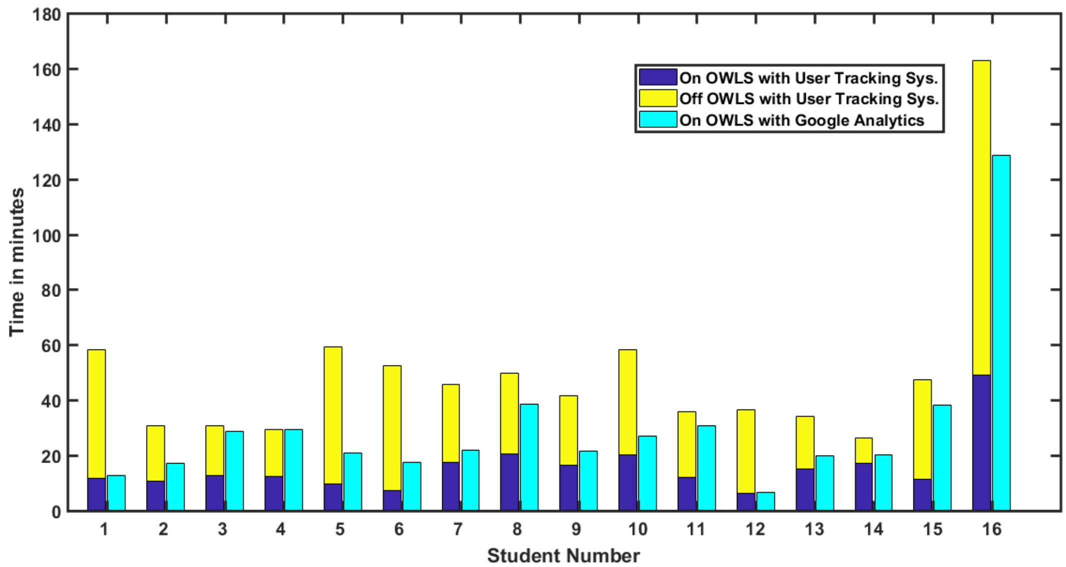

Figure 7. The user-tracking system compared to the earlier Google Analytics-based system.

6. Conclusion

In this paper, the authors have presented the following: a) the functionalities of a secure individualized user-tracking system developed within a cyberlearning system, b) the design of an OWLS-based environmental monitoring task implemented within a classroom environment for in-class field site visit and laboratory experience, c) the pilot study to investigate the relationship between individualized students' behavioral engagement and learning for the specific OWLS-based learning task, and d) the efficiency of the custom user-tracking system in comparison to Google-Analytics based user-tracking system used within a cyberlearning system to capture individual student's behavioral engagement.

The custom user-tracking system is developed to collect in-depth information about each student's interaction within the system. The data collected are analyzed to find insights about individualized behavioral engagement and its relationship with learning. In prior studies, time spent on a task has been regarded as a measure of behavioral engagement [14], however, this study identified a better measure of behavioral engagement time by including a unique feature in the user-tracking system that detects whether a user is using the OWLS browser or not. A comparison of the engagement time detected by the user-tracking system and Google Analytics-based system showed that for all the students, Google Analytics-based system overestimated the engagement time with the OWLS, providing evidence for the efficiency of the user-tracking system. Moreover, overcoming the limitation of the Google Analytics-based system, this user-tracking system is capable of detecting individual users across devices, browsers, and operating systems.

Overall, the design of the OWLS-based task and its pilot implementation was useful in testing out the user-tracking system in a classroom environment and exploring various approaches to analyze the user-tracking data. The development and implementation of the OWLS-based learning task demonstrate how a cyberlearning tool, like the OWLS, can be utilized in a hybrid instruction mode (i.e., classroom lessons amplified by the use of technology) for imparting in-class field visit and laboratory experience. Students spent more time outside the OWLS than on the OWLS to analyze the environmental data and writing the findings in the report on the OWLS-based task. It was found that the Off OWLS time is significantly and positively correlated with the learning score at the 0.05 level of significance. This result indicates that students spending more time on analyzing the data and writing the report, outside the OWLS, performed better on the learning task. Again, the On OWLS time was significantly and positively correlated to the number of clicks on the OWLS at the 0.01 level of significance, indicating that either of them can be considered for measuring the level of engagement within the OWLS. In addition, data visualization was used to explore the various actions and behaviors portrayed by each of the students to complete the OWLS-based task. Data mining algorithms will be used to further detect various common patterns/ strategies taken by students to complete the task [54], [55]. Furthermore, the analysis of resource utilization of the OWLS components by each student portrayed that the students mostly used the components that were required for the task, in comparison to the other components. A poster based on this work was presented at the meeting of the Grand Challenges Scholars Program (GCSP) at the National Academy of Engineering (NAE) in Washington, D.C [57].

This study has motivated the authors to continue this research with a larger sample size. This will also allow examination of the effect of various variables (gender, familiarity with the OWLS, proficiency level of the students, etc.) that might affect students' learning and engagement with the OWLS. According to literature, the behavioral engagement captured by the user-tracking data might be related to how students perceive their engagement with the system [58]. To examine this relationship, the authors are investigating use of a user engagement scale for measuring the perceived engagement and the results will be a presented in forthcoming papers.

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Appendix A. OWLS-based environmental monitoring task

Webb-Branch-Watershed-based Environmental Monitoring Task

The Learning Enhanced Watershed Assessment System (LEWAS) is a unique real-time water and weather monitoring system that has been developed at at Virginia Tech in Blacksburg to enhance watershed monitoring education and research. LEWAS field site has environmental instruments including an acoustic Doppler current profiler, a water quality sonde and a weather station, each taking measurements every 1-3 min continuously for 24 hours. LEWAS has an open-ended, guided cyberlearning environment called the OWLS. It delivers integrated live and/or historical environmental data from the LEWAS instruments to end users via the following link: http://owls.lewas.ictas.vt.edu/login. The OWLS has been designed so that a user can explore its various components to learn about the LEWAS and its field site, the Webb-Branch, the environmental parameters, changes in its environmental parameters over time, to understand different environmental events, to download data for calculations, and to compare, contrast and analyze the environmental data.

In this OWLS-based assignment, you will focus on remotely conducting continuous environmental monitoring of the Webb Branch watershed using the OWLS. Please use the supporting evidences of data, graphs and/or imagery from the OWLS to answer the following 3 questions:

1. **Describe the Webb-Branch**

Describe the Webb-Branch including its area and other details that you can find within the OWLS. Also, describe the current condition of water quality of the LEWAS field site relative to what you can observe for the water quality parameters of the last 6 days. Clearly indicate the dates for this investigation.

2. **What are the benefits of Continuous Environmental Monitoring Data?**

Explore the OWLS to discuss the benefits using a specific example available from OWLS case studies.

3. **Select and analyze an Environmental Event shown on the OWLS:**

Find a 3 hour specific conductance event from the OWLS, where the specific conductance value was more than 40000 µS/cm and analyze it. Specifically, find the start, end time of the event. Find the highest specific conductance value during the event. Find the average specific conductance values during and after the event. Show relevant graph and imagery of the event. Reflect on how it might affect the aquatic species in the Webb Branch watershed. Support your conclusions.

Appendix B. Rubric for the OWLS-based environmental monitoring task

Topic	*Subtopics*	*1 point*	*2 points*	*3 points*
Describe the Webb-Branch (8 points)	Watershed Description	One line description	Average description	Thorough description
	Area	Present		
	Description of the current condition of water quality of the LEWAS field site	Description includes qualitative/quantitative description without too much analysis	Description includes both quantitative and qualitative description with good analysis	Description includes quantitative and qualitative description with evidences of pictures/graphs
	Clearly indicate the dates for this investigation	Exact dates present		
What are the benefits of Continuous Environmental Monitoring Data? (6 points)	Benefit discussion	One benefit presented	Two benefits presented	More than two benefits presented
	Case study example	Case study mentioned	Case study mentioned and discussed well qualitatively/quantitatively	Case study mentioned and discussed qualitatively and quantitatively with evidences of pictures/graphs
Select and analyze an Environmental Event shown on the System 1 (8 points)	Start and end time of the event	Presented (Answer: around 1.30 - 4.30am on April 18)		
	Highest specific conductance value during the event	Presented (429000 microS/cm at 2.39 am)		
	Average specific conductance values during the event	Values presented (around 12100microS/cm)		
	Average specific conductance	Values presented (around 1770.9microS/cm)	Values presented with graph and imagery	

	values after the event			
	Reflect on how it might affect the aquatic species in the Webb Branch watershed	Moderate reflection	In-depth reflection	