Investigation of Personalized Learning and Engagement within a Cyberlearning System for Environmental Monitoring Education

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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 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 doctoral research aims to investigate personalized learning and engagement within a cyberlearning system, called the Online Watershed Learning System (OWLS). This cyberlearning system utilizes learning resources generated by a real-time high-frequency environmental monitoring system, called the Learning Enhanced Watershed Assessment System (LEWAS).

The goals include advancing the OWLS with a user tracking system and data availability and visualization features and investigating personalized learning and engagement within the OWLS. A user-tracking system is developed utilizing a Node.js-based Express framework and deployed in the LEWAS server, which identifies individual users across devices such as laptops, tablets, and desktops, and detects their interaction within the OWLS, and stores the interaction data in a PostgreSQL database. HTML, CSS, and JavaScript technologies are used for the client-side development. Informed by the situative theory of learning and engagement theory, investigation was carried out with 52 students from a junior-level civil engineering class. They completed an OWLS-based in-class task focused on concepts related to the environmental monitoring. Pre and post-surveys and the user-tracking system were utilized to collect data on individual student's perceived and conceptual learning, perceived and behavioral engagement, and perception towards the learning value of the OWLS. Results provide several insights into individual student's learning and engagement with the OWLS. For example, students gained knowledge using the OWLS, and their learning varied with the design of the in-class task, which, however, did not impact their engagement. Further, students' learning (scores on in-class task) had a significant negative relationship with their behavioral engagement (frequency of resource utilization of the OWLS). Additionally, temporal navigational strategies of 52 students were identified on an individual basis. Finally, variations in learning and engagement were analyzed in terms of factors such as gender and background knowledge. The study has implications for designing effective cyberlearning systems and learning activities that can utilize cyberlearning systems for leveraging technology-enhanced teaching and learning.

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GENERAL AUDIENCE ABSTRACT

Individuals differ in their approaches to learning. For the success of diverse group of learners, the National Academy of Engineering has identified "Advance Personalized Learning" as one of the 14 grand challenges. One possible approach for this advancement is to utilize online learning technologies, such as cyberlearning systems that provide the affordance to uniquely identify each learner and track his/her learning progress allowing an investigator to understand the differences in the learning process of individuals. Motivated by this idea, an interactive cyberlearning system, called the Online Watershed Learning System (OWLS) has been utilized in this study. It contains learning resources generated by a real-time high-frequency environmental monitoring system, called the Learning Enhanced Watershed Assessment System (LEWAS). The goals of the study include: 1) advancing the OWLS with a user tracking system and data availability and visualization features and 2) investigating personalized learning and engagement within the OWLS. For goal 1, cutting-edge technologies were utilized so that OWLS with its user-tracking system can be accessible by large number of users using modern web browsers on devices, such as laptops, tablets and cell phones. For goal 2, classroom implementation was carried out with 52 junior-level civil engineering students, who completed an OWLS-based environmental monitoring task within the class time. Results provide several insights into variation of individual student's learning and engagement with the OWLS. For example, students gained knowledge using the OWLS, and their learning varied with the design of the in-class task, which, however, did not impact their engagement. Additionally, temporal navigational strategies of 52 students were identified on an individual basis. Variations in learning and engagement were also analyzed in terms of factors such as gender and background knowledge. The study has implications for designing effective cyberlearning systems and learning activities that can utilize cyberlearning system for leveraging technology-enhanced teaching and learning.

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Chapter 1: Introduction

1.1 Introduction and Motivation

> *"It is impossible to redesign students to fit into a system, but we can re*-design a system for *students. This can be the difference between success or failure for our students that need the promise of higher education the most."- Joseph South* (U.S. Department of Education, 2017b)

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), proposed by the U.S. Department of Education, suggested that for every level of education, institutions should utilize technologies to facilitate education anywhere and at any time (U.S. Department of Education, 2017a). Specifically, for the success of American postsecondary students, that currently include students from diverse socioeconomic and ethnic backgrounds, genders, age-groups and learning needs, the supplement of the NETP report in the context of higher education recommends that for improving the learning experiences of such diverse group of students, technologies should be used for leveraging student-centered approaches of teaching and learning (U.S. Department of Education, 2017a) . These approaches are beneficial to promote personalized learning experiences by placing active role on the students and making them the agents of their own learning (Liñán & Pérez, 2015). To assess individual competencies, the NETP report recommends: "collect and use real-time learning data to provide targeted assistance to students" (U.S. Department of Education, 2017b, p. 11). Further, the report highlights the need to utilize technology-enabled assessments that will support students "to learn and practice the skills they need to apply their knowledge in the real world and should provide institutions with data and tools for improving teaching and tracking progress" (U.S. Department of Education, 2017b, p. 38). Such assessments are known to improve students' learning and promote personalized learning (Liu, Wong & Hui, 2003). It may be noted in this context that advance personalized learning is one of the 14 grand challenges of engineering (National Academy of Engineering, 2017). Personalized learning is essential to manage the differences that exist between learners, who can be self-driven or may need structured instructions or may be motivated by external rewards. The first step towards advancing personalized learning is to understand the differences in the learning process of individuals. For this purpose, internet-based education technologies offer the affordance to develop personalized learning spaces, where learners can be uniquely identified and their progress can be tracked (Martinez, 2002).

Cyberlearning systems are a new learning infrastructure that use networked computing along with communication technology to support teaching and learning (Alvarez, Silva, & Correia, 2016; London, 2012). An NSF Taskforce on Cyberlearning mentions that cyberlearning systems are capable to help learners from various backgrounds, to learn from anywhere around the globe and at any time, from both inside and outside of traditional classroom spaces (Borgman et al., 2008; Madhavan & Lindsay, 2014). Cyberlearning systems utilize new ways for knowledge sharing utlizing multimedia that integrates texts, audio, video, and applications. It can be accessed from various devices, such as personal desktops, laptops, smartphones, and tablets to support teaching and learning. Using a networked interface, cyberlearning tools can be used as a shared resource across different countries and/or institutions, thereby offering learning opportunities to a large number of learners (Bos et al., 2007).

To provide students with personalized learning experiences, cyberlearning systems actively engage individual students in the learning process (London, 2012; Madhavan's commentary in Johri and Olds, 2011). For example, 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 (Heradio et al., 2016; Henke & Wuttke, 2013). Heradio et al. (2016) note that traditionally, evaluation of cyberlearning systems for pedagogical effectiveness has been the focus of various researchers. In recent years, cyberlearning systems are being equipped with user-tracking capabilities, thus enabling to investigate the individualized learning processes. These tracking methods can collect and store the digitized traces of individual students (Rieh, Collins-Thompson, Hansen & Lee, 2016). These traces can be denoted by the time sequence of actions completed by a user/learner, such as mouse clicks and navigational patterns over web-pages (Omar & Zakaria, 2012). Analysis of the logged student data helps in identifying the preferences and bottlenecks tackled by each learner (Madhavan's commentary in Johri and Olds, 2011). It can also explain the level of engagement of the students within the cyberlearning platform (Baltierra et al., 2016), their study habits (Branch & Butterfield, 2015) and their patterns of inquiry while solving a problem (Kinnebrew & Biswas, 2012). These in-depth continuous assessments can allow educators to evaluate individual students' performances, provide appropriate feedback, understand the efficiency of the learning resources, and validate/evaluate the instructional methods, which can inform the quality of education, and lay the foundation for a more effective technology-infused education system (Romero & Ventura, 2010). Heradio et al. (2016) believe that this approach of analyzing user-tracking data "enables deeper levels of assessment unseen to date" (p. 34). Several other researchers have suggested that the approach of understanding students' learning utilizing these user-tracking data will be a major research topic for the upcoming years (Liñán & Pérez, 2015; Papamitsiou & Economides, 2014; Romero & Ventura, 2013). 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.

Within this context, this research extends the prior engineering education research works completed (Brogan, 2017; Brogan, Lohani & Dymond, 2014; Brogan, McDonald, Lohani, Dymond & Bradnar, 2016; McDonald, Lohani, Dymond & Brogan , 2015; McDonald, Brogan, Lohani, Dymond, Clark, 2015) at the Learning Enhanced Watershed assessment System (LEWAS) lab. The LEWAS lab is a high-frequency, real-time environmental monitoring system located at Virginia Tech. The latest research is related to the development and evaluation of an Online Watershed Learning System (OWLS), which is a LEWAS-based cyberlearning tool (Brogan, 2017). It is an interactive open-ended guided cyberlearning system delivering integrated live and/or historical environmental monitoring data from the LEWAS to end users regardless of the hardware and software platforms used.

This dissertation work focuses on extending the research in the LEWAS lab in the context of personalized learning. Specifically, it aims at advancing the research potential of the OWLS by developing an individualized user tracking system and adding new data visualization and availability features (Brogan, Basu & Lohani, 2017). Additionally, it aims to explore how individual students engage and learn within a cyberlearning system, and how variation in engagement relates to the learning outcome within a blended classroom environment for environmental monitoring education. Situative theory of learning and engagement theory has been utilized to understand students' learning and engagement. The study is also informed by the literature on learning analytics and educational data mining. The rest of the chapter includes the following. Section 1.2 includes the definition of key terms that are used throughout the dissertation. Section 1.3 presents the research goals and the background of this research work. Finally, section 1.4 highlights the research phases and the organization of the dissertation.

1.2 Definitions of the Key Terms

Cyberlearning system: Cyberlearning system is an innovative learning infrastructure that uses networked computing along with communication technology to support teaching and learning (Alvarez, Silva, & Correia, 2016; London, 2012). It can be used as an online learning tool within and outside traditional classroom spaces for teaching and learning.

LEWAS: Learning Enhanced Watershed Assessment System (LEWAS) is a high-frequency, real-time environmental monitoring system collecting water quantity and quality, and weather data to monitor the Webb Branch Watershed (~3 sq. km.), which is located on the campus of Virginia Tech (McDonald, Dymond, Lohani, Brogan, & Clark, 2014). An interdisciplinary group of faculty and students (graduates and undergraduates) leads the development and maintenance of this system.

OWLS: Online Watershed Learning System (OWLS) is an interactive open-ended guided cyberlearning system of the LEWAS that enables users to monitor the environmental changes on the Webb Branch watershed, and access historical and real-time data, and case-studies for research and education (Brogan, 2017). It has several learning resources (components), such as single graph, watershed summary and case studies.

User-tracking data and system: User-tracking data, also referred to as trace data are timestamped sequence of objects and actions utilized by a particular user when accessing a system (Omar & Zakaria, 2012). Within a cyberlearning system, these user-tracking data can provide information about the interaction between human and the computer-mediated system. A system that can collect these user-tracking data and store it for future analysis is called a user-tracking system.

Engagement: Engagement results from how an individual feel, think and behave within a specific context and is reactive to the changes in the learning environment (Connell, 1990 in Fredricks, Blumenfeld & Paris, 2004). Within the context of Human-Computer Interaction (HCI), engagement is defined as the human response to computer-mediated interactive systems (O'Brien & Cairns, 2016), which in this case is the OWLS.

Behavioral Engagement: The participation and the interaction exhibited by users within a computer-mediated interactive system (e.g., OWLS) is called the behavioral engagement (O'Brien & Cairns, 2016). It is measured to understand users' actions within the OWLS.

Perceived Engagement: Students' perceptions of the attributes of engagement, which are the characteristics of human-computer interaction impacting students' behavioral engagement is called the perceived engagement in this study. It measures the psychological state of students' engagement with the OWLS (O'Brien & Toms, 2008). For example, aesthetics is an attribute of engagement. A student's thought on aesthetic of a system can influence the way he/she behaviorally engages within the system.

OWLS-based Conceptual Learning Outcome: It is the learning outcome achieved after students go through an OWLS-based intervention. In this study, the conceptual learning is measured with the scores students receive on an OWLS-based task during the intervention.

Perceived Learning: Students' perceptions of their learning with the OWLS are termed as perceived learning. It is used an indirect measurement for understanding students' learning (Nickerson, Corter, Esche & Chassapis, 2007).

Perceived Learning Value of the OWLS Components: Students' perceptions/views about the significance of each of the OWLS component for learning are termed as the perceived learning value of the OWLS components. It is measured to evaluate the importance of each of the OWLS components (Brogan, 2017).

1.3 Research Goals

The key goals are explained in the context of the innovation cycle of educational research and practice (see figure 1-1) (Jamieson & Lohmann, 2009). The first cycle, which began in 2007-08 resulted in the development of the LEWAS research lab and led to the first PhD dissertation in this lab that dealt with the evaluation of students' motivational gain due to remote access of live environmental data (Delgoshaei, 2012; Delgoshaei & Lohani, 2014). During the second cycle that began in 2013, the OWLS was developed. Classroom testing of the OWLS led to the evaluation of the effectiveness of the OWLS in increasing students' learning and motivation in environmental monitoring education (Brogan, 2017; Brogan, Lohani & Dymond, 2014; Brogan et al., 2016; McDonald et al., 2015; McDonald et al., 2015). This study, initiated in 2016, constitutes the third cycle building on the finding of the prior cycle and addressing the need for in-depth assessment of individual students' learning and engagement within the OWLS. The research has the following two major goals (figure 1-1):

1) Advancement of the Online Watershed Learning System (OWLS)

2) Investigation of personalized learning and engagement within the OWLS for environmental monitoring education

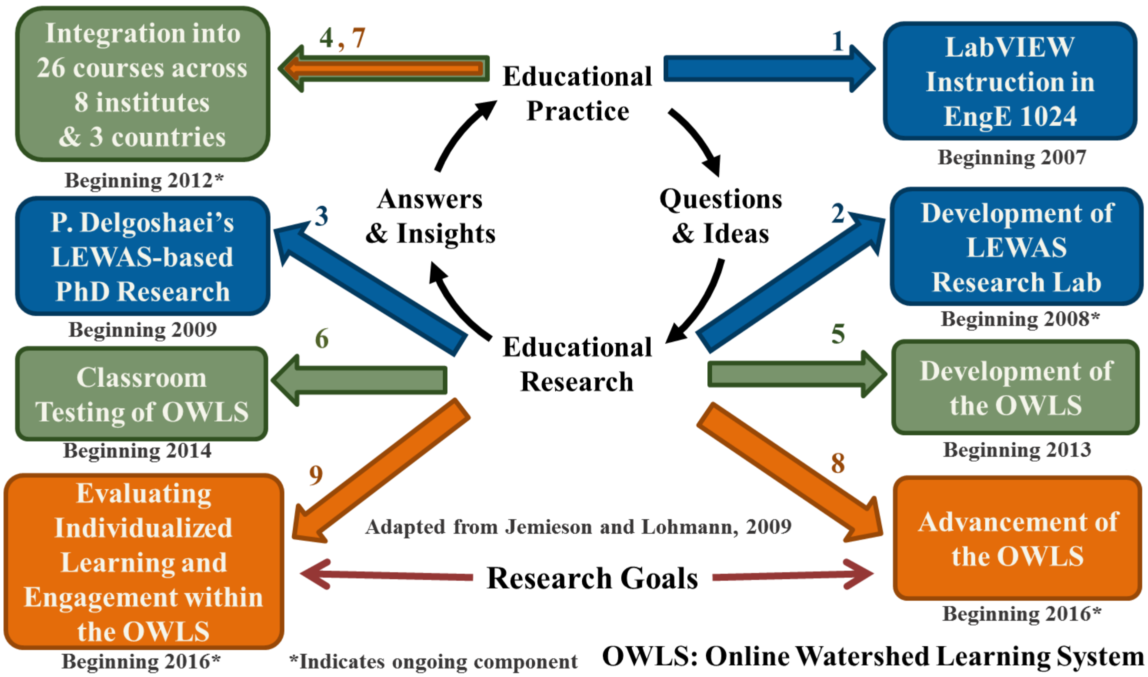


Figure 1-1. Innovation cycle of educational research and practice- implemented at the LEWAS lab. The dates for each block are the beginning time of that block. For blocks 1-3, see (Delgoshaei , Lohani, & Green, 2010; Delgoshaei & Lohani, 2012, 2014; Delgoshaei, 2012; Lohani, Delgoshaei , & Green, 2009). For block 4, see (Dymond , Lohani, Brogan, & Martinez, 2013; McDonald, Brogan, Lohani, Dymond, 2015; McDonald, Brogan, Lohani, Dymond, & Clark, 2015; McDonald, Dymond, Lohani, Brogan, & Clark, 2014; McDonald, Lohani, Dymond, & Brogan, 2015). For blocks 5 and 6, see (Basu, Purviance, Maczka, Brogan, & Lohani, 2015; Brogan et al., 2014; Brogan, 2017; Brogan, McDonald, Lohani, Dymond, & Bradner, 2016; McDonald et al., 2015) and 8 and 9, see (Brogan, Basu and Lohani, 2016).

1.3.1 Background of the LEWAS lab and Prior Research Work

The LEWAS lab is a unique real-time high-frequency environmental monitoring lab established to promote environmental monitoring education and research (Delgoshaei, 2012; Delgoshaei & Lohani, 2014; McDonald et al., 2015; Brogan et al., 2016). The lab was initiated as a part of a PhD dissertation in Engineering Education Department at Virginia Tech (Delgoshaei, 2012; Delgoshaei and Lohani, 2014). Delgoshaei (2012) adapted four types of expectancy-value (i.e., intrinsic, attainment, utility and cost value) (Li, McCoach, Swaminathan & Tang, 2008) to evaluate learning effectiveness of the LEWAS-based learning modules implemented in a freshman level engineering course. It was found that experience to learn from real-time data increased students' interest and their views of the feasibility of environmental monitoring. Since 2008, this system has gone from a prototype system utilized in a freshman level class to a real-time environmental monitoring system that has now been used in at least 33 courses (freshman to graduate level) across 9 institutions and in 3 countries (Basu et al., 2015; Brogan, Basu & Lohani, 2017).

LEWAS Lab. The LEWAS lab has a field site (Figure 1-2) located at the outlet of a small creek (Webb Branch), which flows through the Virginia Tech campus (McDonald et al., 2014). This stream joins a water quality impaired stream, Stroubles Creek (Virginia Department of Environmental Quality, 2006). Webb Branch was chosen as the field site because of its environmental significance and also due to its closeness to the campus (Clarke et al., 2013). There are multiple instruments installed at the field site for monitoring the environment. These include: a weather station and a rain gauge to monitor weather conditions, an ultrasonic transducer and a flow meter to measure stream flow, a sonde to monitor water quality and a camera to offer a visual reference to the measured parameters. These instruments take measurements every 1-3 min of environmental data including water turbidity, pH, dissolved oxygen, temperature, flow rate, air temperature and humidity. The field site utilizes power from both the grid and a couple of photovoltaic panels and connects to the campus wireless network using a high-gain antenna for transmitting the environmental data collected from instruments. The LEWAS includes the following four stages (Basu et al., 2015; Brogan et al., 2014): 1) environmental monitoring instruments, 2) data processing, 3) data storage and 4) end-user interface, which enables users to visualize and use LEWAS data, e.g., the OWLS, for research and education.

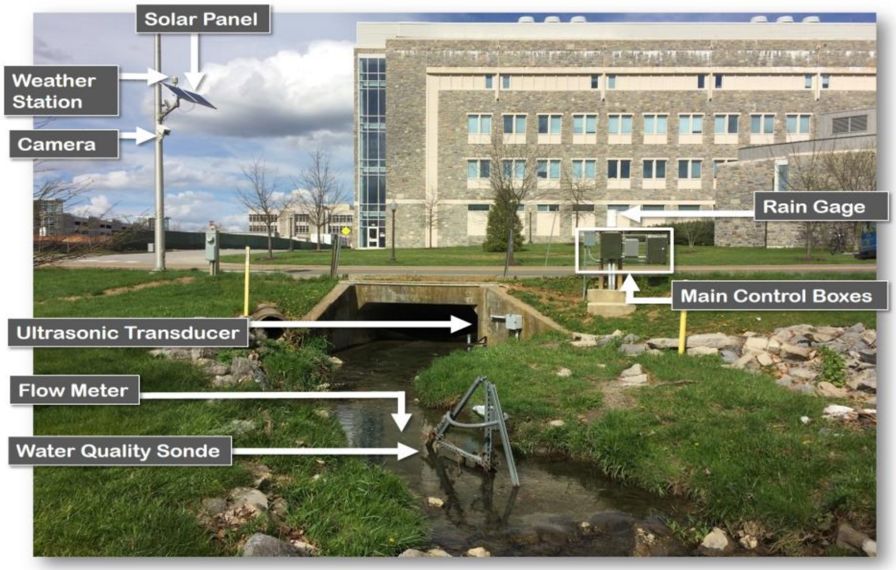


Figure 1-2. LEWAS lab field site.

The Online Watershed Learning System (OWLS). The OWLS (Figure 1-3) is an interactive open-ended guided cyberlearning system that delivers integrated live and/or historical environmental monitoring data from the LEWAS and LEWAS data-based case-studies to end users regardless of the hardware and software platforms used. The OWLS was developed with the following features: 1) remotely situates users from anywhere around the world at the LEWAS field site, 2) works on several hardware and software platforms, 3) does not necessitates installation of any software, 4) adds the ability to observe and download historical data until last 31 days and 5) not affected when accessed simultaneously by a large number of users. It was accessible from the following link: https://www.lewas.centers.vt.edu/dataviewer/index.html. Table 1-1 describes various components of the OWLS and lists the intended purpose for each component (Brogan et al., 2014; Brogan et al., 2016). The advancement of the OWLS, one of the goal of this study, builds on these components of the OWLS.

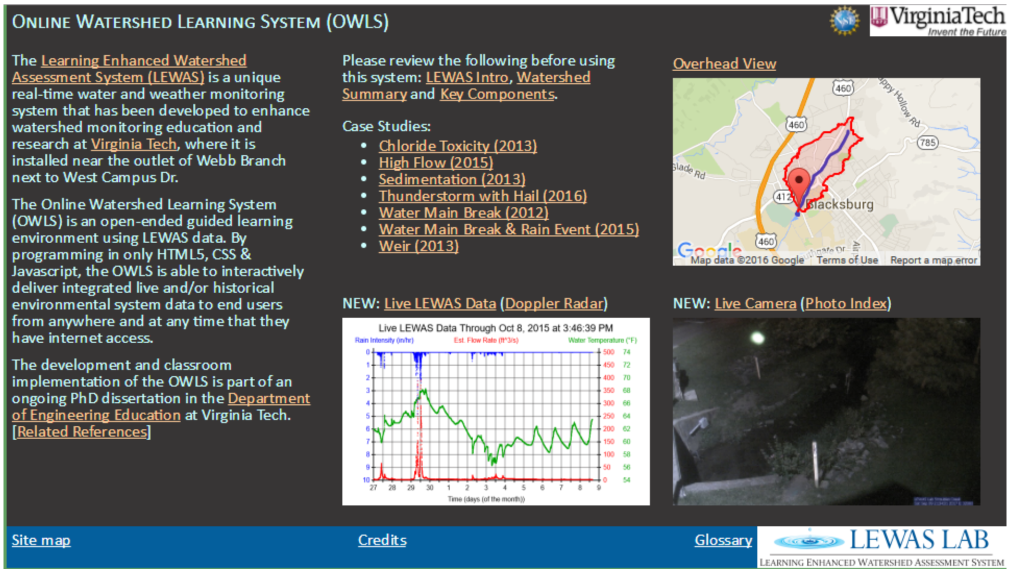


Figure 1-3. The Online Watershed Learning System (OWLS)

Table 1-1. Various components of the OWLS with its intended purposes

OWLS Components (14 altogether)	**Purpose (Broader categories)**
Live LEWAS data (single_graph.html) and Data Download from anywhere, anytime for current 31 days	Data availability
Interactive Graphs (single_graph.html), Live Camera, Weather Radar and Storm View	Data visualization
Overhead View/Map, LEWAS Intro, Case Studies, Photo Index, Glassary, Watershed Summary	Supporting information
How-to-use Guide (site map), Home (index), Key Components	Operating instructions

Prior OWLS-based Engineering Education Research. Prior studies with the OWLS have been conducted at different academic levels to assess its effectiveness in increasing students' learning of environmental monitoring concepts and their motivation to study those topics. Brogan et al. (2014; Brogan et al., 2016; McDonald et al., 2014; McDonald et al., 2015) used the situated learning theory (Newstetter & Svinicki, 2014) to assess the impact of the OWLS/LEWAS on students' learning of community college freshmen, university seniors and graduate students. To measure the learning outcomes, a set of concept inventory questions at the undergraduate level were developed and these were mapped to various levels of Bloom's Revised Cognitive Taxonomy (Brogan et al., 2014; Brogan et al., 2016; McDonald et al., 2014; McDonald et al., 2015). Further, in order to examine the effect of OWLS on students' motivation, a MUSIC Model of Academic Motivation (Jones, 2009) was employed. The OWLS has been implemented from Fall 2012 to Fall 2015 for teaching environmental monitoring concepts to community college students (freshmen) in general engineering courses, and senior and graduate level civil and environmental engineering students in hydrology courses (Dymond et al., 2013; McDonald et al., 2014). Findings suggest that students perceived the most learning value from the data availability and data visualization components of OWLS compared to the other components listed in Table 1-1. Also, the use of LEWAS and/or OWLS resulted in learning gain and enhanced motivation in environmental monitoring concepts for most of the student groups at various academic levels.

An anonymous user tracking was implemented within the OWLS with Google Analytics (Brogan, 2017). This tracking capability was pilot tested in two freshmen engineering courses at a community college during the fall 2015 semester. Roughly 80 students from a total of four sections participated in the study. The tracking data included a unique user id (UUID), time of visit, URL visited, city of the user, operating system, and browser and version. The unique user id identified each user but could not track individual users across devices. Consequently, "groups of users" from four sections of the community college as well as across the world were identified using the OWLS system. The usage of various components of the OWLS by each student group was also found out. User-tracking data showed that groups of students tend to use the data visualization and data availability components for the maximum time. These components also ranked high according to the students' perceived value for different components of the OWLS (Brogan, Basu & Lohani, 2017). It was suspected that the students' usage and ranking of the components of the OWLS may be impacted by the direction given by the instructor to use the Interactive Graph and Live Camera views during the in-class time, which increased their exposure to these pages compared to the other pages.

1.3.2 Goal 1: Advancement of the OWLS

The research and education scope of the OWLS is advanced by adding the following features:

1) Addition of a user-tracking system with login functionalities that have the following features:

   a. track an individual user across various devices, such as desktops, laptops and tablets

   b. track the temporal navigation pattern of an individual user within the OWLS as well as his/her actions and selections within a webpage with corresponding timestamp

   c. track at a regular interval of time, whether a user is using the OWLS browser or not and log his/her status, which will be beneficial in improving the time estimate of the OWLS utilization

   d. store an individual user's login information and his/her user-tracking data in a secure database in the LEWAS server rather than in a proprietary server, such as Google Analytics that was used earlier

   e. compatible with various devices, browsers and operating systems of the users without installation of additional software

   f. robust to collect and store information of a large number of users

2) New data availability features (such as date picker and data download button) that will allow users to view (in graphical and tabular format) and download historic and current LEWAS environmental data for maximum three parameters for any date range in csv format.

3) New data visualization features (such as data point selection and transition) that will provide users with more options and flexibility for observing various environmental data.

The user tracking system is developed to address the limitation of the Google Analytics-based system that could not track individual users across devices. The user-tracking system is beneficial in collecting trace data on how the OWLS is being utilized by large number of users to complete OWLS-based tasks on an individual basis. Compared to many existing user-tracking system that only logs users' requests on the server-side, this system tracks users' actions on the browsers or client-side (May & George, 2011). To fully capture users' actions on the OWLS browser, the tracking system collects both the process of interaction (button clicking, playing videos) and its product (name of the environmental parameter chosen) information. All these users' data are securely stored in a LEWAS database, which makes the OWLS a secure learning environment for the users. This addresses the concern of protecting sensitive personal data within a cyberlearning system (May & George, 2011). The user tracking system is used as a tool to collect user-tracking data.

Considering the learning value perceived by the students for the data availability and visualization components of the OWLS in its previous implementations, and understanding the benefit of data visualization features within cyberlearning systems (discussed in section 2.2 of the literature review chapter), it is determined that adding more of these two components will enhance the engagement and effectiveness of the OWLS. This will allow users to interact and interpret the reality of the remote LEWAS field site through the OWLS in a flexible way. The advancements of the OWLS is explained in details in Chapter 3.

1.3.3 Goal 2: Investigation of Personalized Learning and Engagement within the OWLS for Environmental Monitoring Education

The primary focus of this goal is to better understand how individual students learn and engage within the OWLS. The overarching research question is:

- *How do individual students learn and engage within a cyberlearning system (i.e., OWLS) to complete an environmental monitoring task?*

During the earlier study with the OWLS, learning gains were not statistically significant and it was suspected to be caused by the LEWAS rather than the OWLS (Brogan, 2017). Therefore, there was a need to understand students' learning gain solely with the OWLS, which is the first objective of this goal. Moreover, in-depth assessment of how individual students engage with the OWLS to learn about environmental monitoring was not explored, which is the second objective of the study. The third objective of the goal is to understand the relationship between students' learning and engagement. Figure 1-4 shows the different types of data that is captured in this study for understanding individual students' learning and engagement within the OWLS. For assessing students' learning, their perceived learning and conceptual learning will be measured. For engagement, students' perceived engagement and behavioral engagement will be measured. Moreover, students' perceptions towards the learning value of various components of the OWLS will also be collected to evaluate the OWLS as a cyberlearning tool. The analysis of these different types of data and evaluation of the relationship between these data is helpful in understanding individual student's learning and engagement within the OWLS for an environmental monitoring task. The context of this study is within a classroom environment where individual students utilize the OWLS for completing an environmental monitoring task.

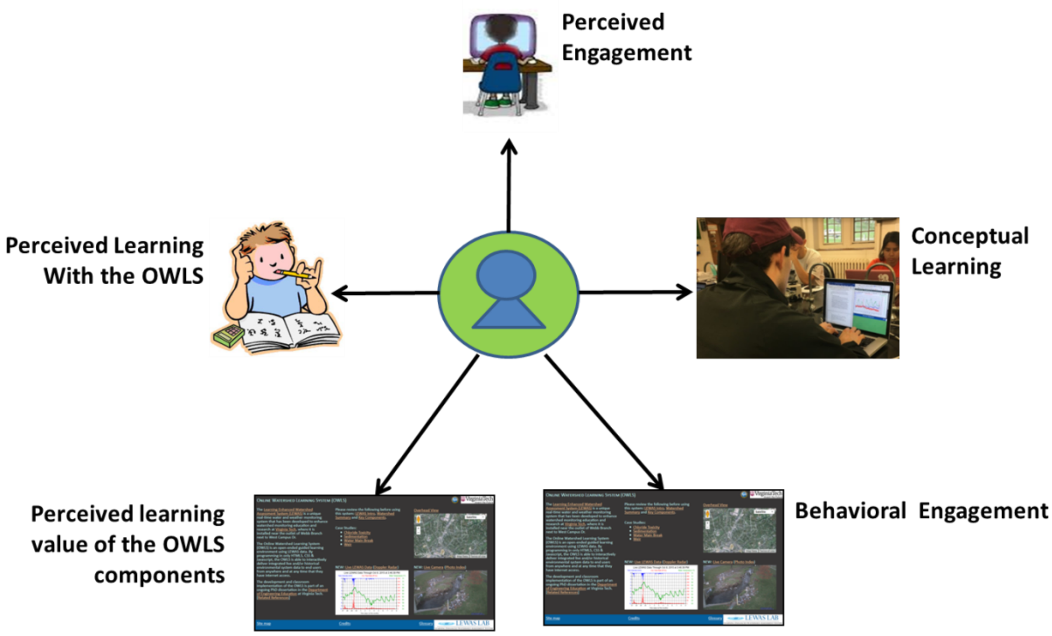


Figure 1-4. Types of data for understanding students' learning and engagement within the OWLS

1.4 Research Phases

To meet the two research goals, the study was completed with the following seven research phases: 1) advancement of the OWLS- part I, 2) pilot study design and implementation, 3) pilot data analysis and plan final research design, 4) advancement of the OWLS- part II, 5) final data collection, 6) final analysis, and 7) report final results and interpretations (Figure 1-5). Phase 1 was completed with the development of the user tracking system with most of the functionalities. The improvement of the tracking capabilities and the rest of the advancement of the OWLS including addition of data visualization and availability features were completed in phase 4. Phase 2 led to the development of a post-survey, an OWLS-based environmental monitoring task and a rubric in consultation with a domain expert, and subsequent pilot implementation of the OWLS with the user-tracking system. Phase 3 provided an opportunity to understand the scope of the various types of data and the trend in the relationships between the data sets, which helped in designing the final study. Phase 5 included the final data collection. During Phase 6, the data were analyzed and the results were written. Finally, phase 7 included the time for reporting results in this dissertation and interpreting the results. The timeline for each phase are also mentioned in Figure 1-5.

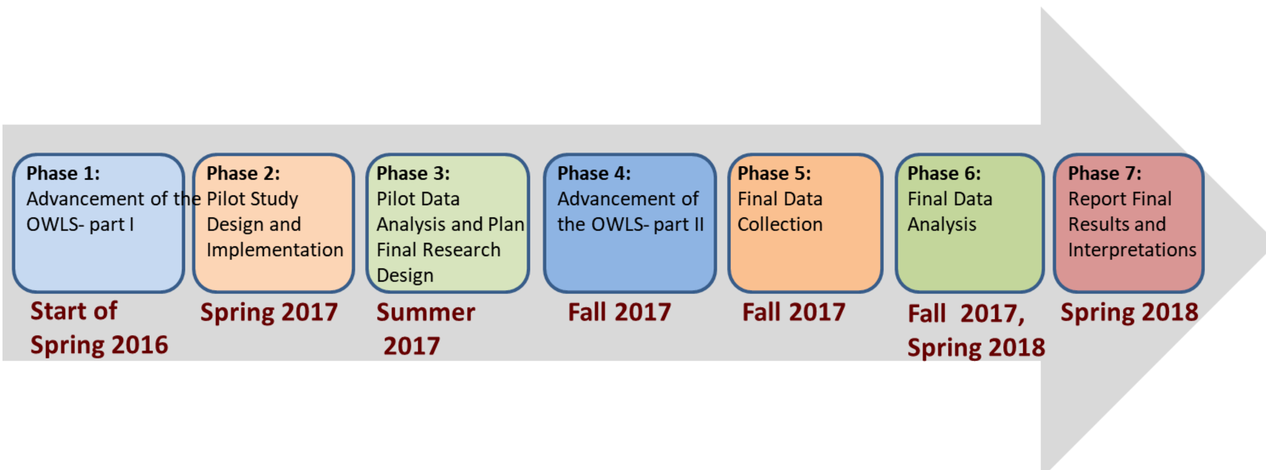


Figure 1-5. Research phases and timeline.

The remaining parts of this dissertation are organized as follows. Chapter 2 includes the review of the relevant literature and the theoretical frameworks for the study. Chapter 3, elaborates on the advancement of the OWLS, which is the first goal of the study. Chapter 4 presents the detailed objectives, method, and results of the pilot study. The detailed method for the final study is included in chapter 5. Chapter 6 presents the results of the final study. Finally, chapter 7 includes the discussion of the contributions of the study from the pilot and final implementations, the limitations, the implications and future directions of the study.

Chapter 2: Literature Review

The literature review in this chapter is organized as follows. In section 2.1, the usefulness of different types of cyberlearning systems used for science and engineering are introduced. The importance of interactive components within cyberlearning system is explained in section 2.1.1 that motivated a part of the developmental component (goal 1) of this study. Section 2.2 situates the research in the context of the environmental monitoring education. In section 2.3, an overview of the field of educational data mining and learning analytics is presented that informs this research. The studies related to analyzing user-tracking data to understand students learning, including user-tracking within Cyberlearning systems, are reviewed in section 2.4. In section 2.5, the two theoretical frameworks, situative theory of learning and engagement theory, utilized in this study are explained. Finally, the section 2.6 includes a summary connecting the literature reviews to this research.

2.1 Cyberlearning Systems

Cyberlearning systems by exploiting network computing and communication technologies have the potential to enhance educational opportunities for a large number student around the world. Whether it is used online courses or integrated within a classroom environment, it brings in flexibility to how students can learn. Cyberlearning systems are significant, particularly in STEM disciplines, as it can be integrated with technologies that allow students' interaction with scientific real-world data, graphical visualizations, remote instruments, virtual manifestations and multimedia components (Borgman et al., 2008). Cyberlearning systems can be of various types including remote laboratories, virtual laboratories, hybrid online laboratories and augmented reality laboratories (Andujar , Mejias, & Marquez, 2011; Balamuralithara & Woods, 2009; Henke & Wuttke, 2013; Ma & Nickerson, 2006; Nedic, Machotkd, & Najhlsk, 2003). Virtual labs refer to simulated labs, which can be used remotely (Balamuralithara & Woods, 2009; Abdulwahed & Nagy, 2011; Caldararu , Patrascu, Caldararu, & Paraschiv, 2003). Virtual labs have been proven to be beneficial in improving student understanding of important engineering concepts (Koretsky, Kelly & Gummer, 2011; Kolloffel & Jong, 2013). In comparison, remote labs typically refer to labs that remotely access physical objects (Andujar, Mejias & Marquez, 2011; Genci, 2009; Hua & Ganz, 2003; Kafadarova , Mileva, & Stoyanova, 2013). Remote labs are becoming popular in engineering and science educational settings because they support: 1) students' interaction with physical environments/equipment and working with real-time data, and 2) learning to handle various kinds of erroneous measurements. It is found in literature that remote labs improve students' engagement, motivation and learning (Sáenz, Chacón, De La Torre, Visioli, & Dormido , 2015; Sell, Rüütmann & Seiler, 2014). Gravier, Fayolle, Bayard, Ates & Lardon (2008) reviewed 42 articles mostly from 2001 to 2007 on remote labs, and presented the current state and future directions of remote labs. Gomes & Bogosyan (2009) presented the state of the remote labs related to industrial electronics education. Additionally, Heradio et al. (2016) have provided a review of the vast literature from 1993 to 2015 on virtual and remote labs using bibliometric techniques. Again, combinations of remote and virtual labs are also in place for several years (Barros , Read & Verdejo, 2008; Choi et al., 2009; Duro et al., 2008), which are classified by Henke et al. (2013) as online hybrid labs. In addition, another type of laboratories is augmented (reality) labs (Andujar et al., 2011; Armstrong & Bennett, 2005; Li, 2010; Borrero & Márquez, 2012; Odeh, Shanab, Anabtawi, & Hodrob, 2012). Augmented labs combine real-time, physical objects with virtual contents. These labs also positively impact students' motivation and engagement (Dunleavy, Dede & Mitchell, 2009).

Compared to all these 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. Therefore, instead of categorizing OWLS into one of the above types, the OWLS is simply regarded as a cyberlearning system in this research, developed in the context of environmental education.

2.1.1 Importance of Interactive Components within Cyberlearning Systems

Cyberlearning systems create an additional layer of mediation between users and equipment, which can affect students' learning as it alters the learning environment. Efforts need to be made to decrease the effect of mediation by connecting the users to the equipment (Lindsay, Naidu & Good, 2007). Cyberlearning systems becomes powerful/effective when these can interactively engage users by integrating multimedia components (Crawford, 2002). Baltierra et al. (2016) emphasized that multiple methods of information delivery needs to be included within a cyberlearning system as the interactivity of various multimedia elements differ. For example, in case of remote labs, multiple multimedia contents (videos, images) need to be used so that the users perceive most of the reality by interacting with remote labs in various ways (Lindsay, Naidu & Good, 2007). Features that can bring flexibility in interacting with scientific data have also proven to be beneficial in engaging individual students to interact with such user interfaces (O' Brien &Toms, 2008). Considering these benefits, as part of this study, data availability features were added to improve users' accessibility to the huge amount of high-frequency environmental data of LEWAS and visualization features were added to provide users' options in observing the LEWAS data that can benefit users' engagement with remote monitoring.

2.2 Need for Environmental Monitoring Education

Covitt , Gunckel & Anderson (2009) highlighted in their paper that "today, all citizens need to be able to understand environmental issues and make informed decisions that will help maintain and protect Earth's life-supporting systems"(p. 38). In this regard, they also mentioned that understanding water, which is a major portion in the environmental system, will help citizens to gain environmental literacy. Again, among the 14 grand challenges announced by the U.S. National Research Council (NRC), which needs solution in 21^{st} century, one is "Provide Access to Clean Water" (Hornberger et al., 2012). In the National Academy of Engineering's "The Engineer of 2020 " report, it is highlighted that the supply of water will affect world's economy and stability in the upcoming years (2004). To address these critical issues, the report emphasizes the need for employing ecologically sustainable practices than can help in preserving the environment for the future. The NAE suggests to find improved ways of protecting and improving water supplies so that the future does not looks grim for billions of people (Schnoor, 2008). To face large-scale environmental challenges in the 21st century, the National Research Council outlined the need for fundamental knowledge of: (i) the sources of contaminants and how they are linked to different types and levels of human activities; (ii) the persistence, transport processes, and degradation mechanisms of these contaminants; and (iii) the risks they pose to the environment and humans (2001). To help students prepare for these challenges, the educational system must help students understand the ways to monitor their environment including water resources, and train them to become future professionals, who have the ability to develop appropriate sustainable solutions.

2.2.1 Environmental Monitoring Education with Student-centered Activities

In order to train students to handle the challenges of the future, classrooms must focus on student-centered approaches that engage the students in hands-on activities (Ngambeki , 2012). The two major challenges of environmental education in the 21st century include: a) integrating student-centered learning activities and field experiences within the classroom, and ii) substituting historical static data with real-time, dynamic, temporally and spatially viable hydrologic systems (Ruddell & Wagener, 2013; Zessner et al., 2011). Two significant themes emerge from previous studies that have examined environmental education for students ranging from grade three through seniors in a college (Armstrong and Bennett, 2005; Iqbal, 2013; Habib, Ma, Williams, Sharif & Hossain, 2012; Fisman , 2005; Bodzin , 2008; Hotaling et al., 2012; Kamarainen et al., 2013; Brogan et al., 2014). The first theme is to include instructional strategies that can benefit student in gaining a more realistic experience by engaging them in real environment, either physically or remotely or virtually where they can comprehend the practicality of the learned theory. The second theme is to leverage technological advancements for incorporating these field experiences into the students' environmental education. Attempts made for environmental monitoring education through active participation of students are discussed below.

2.2.2 Interaction with Real-Environments

Researchers have conducted studies targeted at bringing environmental monitoring issues into the classroom by allowing students to interact with real environment. Fisman (2005) took students from third and fifth grade to visit a local pond to teach them about water quality. Bodzin (2008) followed a similar approach by taking fourth grade students of an after-school program to examine a pond in their schoolyard. Students in this program witnessed man-made pollution objects in the pond, collected pH, temperature and conductivity data from the pond, and analyzed the watershed using GIS and Google Earth software. Investigating a familiar environment, helped students to improve their awareness and responsibility towards their own environment. In a SENSE IT (Student Enabled Network of Sensors for the Environment using Innovative Technology) program, students from the level of middle and high school, calibrated, tested and deployed water quality sensors to collect water salinity (conductivity), temperature, turbidity and depth of local waterways (Hotaling et al., 2012). Overholt and MacKenzie (2005) reviewed a number of projects involving stream monitoring that fifteen high school teachers of five states (Montana, Tennessee, Colorado, Michigan and Ohio) have developed to complement theoretical classroom concepts with practical knowledge. At the undergraduate level, Iqbal (2013) integrated classroom knowledge with experience of physical laboratory analysis of biological, chemical, and hydrological characteristics of different water samples collected by senior students during their field site visits.

2.2.3 Interaction with Virtual and Remote Environments

Virtual environments are also utilized for teaching environmental monitoring concepts. For example, researchers at UCLA found that students, who used the Interactive Site Investigation Software (ISIS) had improved perceived learning gains. The ISIS was used by students to complete field works virtually including creating wells, collecting samples of groundwater, collecting samples for laboratory testing, and carrying out experiments on hydraulic transport (Harmon et al., 2002). Burian et al. (2009) described a virtual lab, which had digital videos of laboratory processes with interactive questions, animated video emphasizing conceptual knowledge and interactive calculators for exploring “what if scenarios” (Burian et al.,2009, p. 14.146.3). It was developed in the University of Utah for the water resource engineering courses. Students of these courses, who utilized the virtual lab components, were able to remember important concepts better than those, who did not have access to it. Barbalios et al. (2016) explained a realistic 3D model supported virtual environment, which aimed to help students to understand the importance of water supplies and to increase their awareness of the problems that arise when a large number of people tries to exploit a limited water resource for their own purposes. It was evaluated in a primary school and found out that it significantly helped in cognitive advancements for the students.

Remote access to real-time environmental data has also been utilized in classrooms for environmental education. For example, Delgoshaei (2012; Delgoshaei and Lohani, 2014) used the Learning Enhanced Watershed Assessment System (LEWAS) as a remote lab to analyze the impact of student experience with real-time watershed data.

Several online hybrid labs that enable interaction with both virtual and remote environments have also previously been used for environmental education. In regards to the water quantity aspect of hydrology education, Habib et al. (2012) investigated the use of a “web-based, student-centered, educational tool called HydroViz designed to support active learning in the field of Engineering Hydrology” (Habib et al., 2012, p. 3778). They attempted to develop “authentic and hands-on inquiry-based activities that can improve students’ learning” (Habib et al., 2012, p. 3771) by using an interactive, web-based platform that integrated in-situ, geospatial and model-generated data. HydroViz constitutes of a combination of remote labs and virtual labs. Another example of online hybrid lab that is used for environmental monitoring education for undergraduate and graduate education is the OWLS (Brogan, 2017; Brogan, Lohani & Dymond, 2014; Brogan et al., 2016; McDonald et al., 2015; McDonald et al., 2015), which is the context of the research. Similar, to previous researches with the OWLS, it will be used within a classroom environment for engaging students in remote environmental monitoring. However, unlike previous research that focused on evaluating the OWLS for students learning, this study focuses on the in-depth assessment of variation in personalized student learning and engagement within the OWLS.

2.3 Educational Data Mining and Learning Analytics

The two interdisciplinary research areas that deal with collection, analysis, and interpretation of educational data to gain a detailed understanding of students' learning are: Educational Data Mining (EDM) and Learning Analytics (LA). Educational data in this context refers to: 1) offline data, for example students' psychological data on how they learn or related to their motivation or their performance data (e.g. course grades) collected within/outside a classroom environment; 2) online user-tracking data collected within online learning environments, such as cyberlearning systems or online courses (e.g., MOOCs) or intelligent tutoring systems (Romero & Ventura, 2010). A huge amount of these educational data provide researchers the opportunity to explore and analyze students' learning in different learning environments with an aim of improving it. Especially the unlimited production and disposal of the online data, identifying students' actions in real-time (e.g., resources usage or temporal navigation), have increased the research potential in these domains (DeBoer, Ho, Stump, & Breslow, 2014). The U.S. Department of Education in their report on "Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics" notes "how analytics and data mining have been—and can be—applied for educational improvement" (U.S. Department of Education, 2012, p. vii). EDM and LA can be used to research and develop strategies and guidelines that have the potential to influence cyberlearning or learning powered by technologies, which are utilized to educate a broad range of students.

EDM is concerned with "developing, researching, and applying computerized methods to detect patterns in large collections of educational data that would otherwise be hard or impossible to analyze due to the enormous volume of data within which they exist" (Romero & Ventura, 2013, p. 12). Its four primary goals (Prakash, Hanumanthappa & Kavitha, 2014) include: a) student modelling to predict students' future learning behaviors depending of various aspects of the students, such as their motivation and attention, b) discovering or improving domain models that depict the learning content and its optimal instructional sequence, c) evaluating the pedagogical support provided by learning technologies, and d) advancing scientific knowledge by testing scientific or educational theories, and generating new research questions. The methods are developed using statistical, data mining and machine-learning techniques for prediction (eg. regression models to predict students' performance from their actions), clustering (e.g. to categorize students according to their actions), relationship mining (e.g. correlational analysis to find relationship between educational variables or sequential pattern mining to analyze students' online sequential actions), distillation of data for human judgement (e.g. drawing data visualization to understand students' learning actions), and discovery with models (using a validated model, for example a machine learning model to find more insights). The findings from EDM studies can have the following application areas: a) predictive to help in decision making, b) generative to develop new or improved learning environments, c) explanatory for scientific discovery about learning and learners (Levy & Wilensky, 2011). Within this area, research is either related to a group of students or individual students. Also, for EDM studies, it is important to consider the following features: time, sequence and context. For example, time represents the length of the session or course, sequence captures the instruction sequence or how students build on their concepts and context indicate the specific learning environment.

According to the 1st international conference on Learning Analytics and Knowledge (LAK), LA is defined as "the measurement collection, analysis and reporting of data about learners and their contexts, for purpose of understanding optimizing learning and environments in which it occurs" (Papamitsiou & Economides, 2014). The focus of learning analytics is not only student performance, but also to assess curricula, departments, and colleges. Data include explicit data of students' actions, such as completing a quiz or taking an exam, and implicit data from their actions, such as online interactions, out-of-class activities, posts on discussion forums, and other activities that are not directly assessed as part of the student's educational progress. LA refers to the inference made from students' learning data to evaluate their academic progress, predict future performance and find the critical issues. It enables instructors and institutions to align educational opportunities to students' academic goals and their capacity. Although, it draws methods from EDM, it also utilizes techniques like social network analysis (study of the online social structure/interaction), sentiment analysis (analysis of students' opinion in a piece of text, such as posts on discussion forums), influence analysis (identifying the influential parameters), discourse analysis (analyzing written, vocal or sign languages), and learner success prediction (developing models that predict success of a student). One of the important application of learning analytics is observing and predicting students' learning performance and finding critical issues early so that interventions can be designed to identify students at risk within a course or a program (Johnson, Smith, Willis, Levine & Haywood, 2011).

Similarity of both these research areas is that, EDM and LA are both concerned with finding meaningful information from the huge amount of educational data to gain insights about students' learning for improving the educational system and benefit the stakeholders that include students, instructors, administrators and researchers. However, the difference between them is that LA takes a holistic approach by analyzing the entire system with its full complexity, while EDM takes a reductionist perspective of dividing a system into components and studying these components in details and their relationships (Papamitsiou & Economides, 2014; Liñán & Parez, 2015). Additionally, EDM emphasizes the development of new computational methods to learn patterns in educational data, and LA focuses on employing the known tools and techniques at large scale on educational data, and reporting the findings for improving student learning and organizational learning systems. For example, techniques within LA are applied at large scale, such as course level, department level or institution level to make decisions, whereas EDM approaches can be used to investigate students' actions in details. As noted by Papamitsiou & Economides (2014), these two research areas are complementary and both these fields should be utilized to gain a holistic understanding and ultimately improving students' learning processes. Again, LA draws from more number of disciplines than EDM. In addition to statistics, psychology, computer science, and the learning sciences, LA is also associated to information science and sociology. According to Liñán & Parez (2015), "their [LA and EDM] differences are partly based on their origin and trends" (p.106). However, contributions from both these fields are necessary to have a broader understanding and complete picture of students' learning. Therefore, this study draws ideas from the research accomplished in both these domains that utilizes user-tracking data in exploring students' learning on online platforms.

2.4 Research with 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 how 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 (Liñán & Pérez, 2015; Baltierra et al., 2016). 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 (Smith, Lange & Huston, 2012; Joksimović, Gašević, Loughin, Kovanović, & Hatala, 2015; Tempelaar, Rienties & Nguyen, 2017). 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 (Liñán & Pérez, 2015). It provides data to understand students' online participation that often aid the management for improving the 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 pages are visited, number of times visited, average duration of each visit, and whether a site has new or returning visitors (Liñán & Pérez, 2015; Baltierra et al., 2016; Brogan, 2017). 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 (Baltierra et al., 2016). 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 (Pardo & Siemens, 2014). 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. However, development of a user-tracking system needs distinctive software design and technologies that often creates a barrier to implement technologies in educational settings (Liu, Calvo, Pardo & Martin, 2015). Among the studies that use custom-user tracking system, they have rarely focused on discussing the technologies used and the rationale behind certain functionalities. This study aims to develop and discuss the technologies of a 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 to understand students' learning within various learning environments including cyberlearning systems.

Several studies have analyzed user-tracking data collected by LMS and investigated the relationship between students' interaction within the LMS and the learning outcome. For example, Ramos and Yudko, (2008) found that the frequency at which students access the resources of an online courses is the predictor of their quiz success. Smith, Lange & Huston (2012) found that login frequency, engagement with course website, grades on assignments, and the speed of adopting learning content are predictors of successful learning outcome. While, Joksimović , Gašević, Loughin, Kovanović & Hatala (2015) found out that the total time spent by students on the system to interact with it has a positive effect on learning outcome, but number of times students contribute on the content of the course was negatively associated with course grades. And, Brozina (2015) found that students, who were using LMS fore frequently are likely to achieve higher grades than rest of the students. Some researchers have combined self-report data and LMS data to have a deeper understanding of students' online engagement and how it is related to their achievement. For example, Pardo, Han & Ellis (2017) have utilized frequency of accessing different kinds of online resources to measure engagement, and self-report to assess self-regulated learning strategies, intrinsic motivation and self-efficacy and found their relationship with academic performance in a blended classroom environment. This study showed that self-reported data explained how students approached their learning experiences and when it is complemented by online engagement indicators, it offered a linear model that explains 32% of variance in academic performance. In addition, there have been several studies that utilized LMS data to explore students' engagement within the context of Massive Open Online Courses (MOOCs). For instance, Fournier, Kop & Sitlia (2011) used learning analytics tool, called Social Network Analysis to analyze quantitative data and used virtual ethnography and focus group to collect qualitative data to get insights about students' learning experiences within a MOOC course. In another study related to MOOCs, authors presented approaches to explain and understand variation in user intention and engagement behaviors by redefining and studying conventional variables like enrollment, participation, curriculum and achievement with user-tracking data. While, Roy, Bermel, Douglas, Diefes-Dux, Richey & Madhavan (2017) have analyzed LMS data on MOOCs environment using a K-means clustering algorithm to group different kinds of learners with an aim to optimize the design of online courses. Compared to the LMS data, the data from a custom user-tracking system used in this study, are both individualized in nature and thus, several approaches used in the above studies, such as self-report data and frequency of resource utilization, have been helpful in drawing conclusions in this study.

Within the context of cyberlearning systems, there is a huge number of literatures, but a few studies have indicated the integration of user-tracking capabilities with their cyberlearning system. For example, some virtual and remote labs (VRL) are integrated with MS for collecting user-tracking data. For example, Sáenz et al. (2015) deployed their UNILAB, which is a collection of 15 remote and virtual labs on automatic control, 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. Restivo et al. (2009) described a remote lab developed as a web-server system based on LabVIEW programming language that was deployed into the Moodle LMS, which helps in storing resources, such as, experiments and tutorials of the labs. Aliane, Martínez, Fraile & Ortiz (2007) have described their remote lab, called LABNET, and indicated their plans for integrating it to the Moodle platform. Senthilkumar (2012) had used some kind of a user tracking system for their remote laboratory. Although they did not mention it explicitly, they have shown usage data for portraying the effectiveness of their remote lab. Marques et al. (2014) described their open remote laboratory, called VISIR, which 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. They found 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 investigates student learning processes.

Here are a few example studies that have integrated a custom user-tracking system to collect their user-tracking data within Cyberlearning systems and focuses on understanding students' learning. Branch & Butterfield (2015) have developed a web-based simulation environment with 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 (Perry & Winne, 2007). 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 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 (2013) 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 (Kinnebrew, Loretz & Biswas, 2013; Levy & Wilensky, 2011). They explored the differential sequential data mining algorithm to identify differentially frequent patterns between high and low performers. Rieh al. (2016) presented how search behaviors or interaction within a system can be helpful in determining the learning behaviors (e.g. comprehending, analyzing and creating) and the corresponding cognitive learning mode (receptive, critical and creative) of a student. Omar & Zakaria (2012) explains how web mining technique can be used to analyze user tracking data for finding usage patterns. They compare three classification algorithms, and conclude that selecting the right algorithm depends on the data and the particular context.

Baltierra et. al (2016) 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. This study has several limitations. First, the researchers asked their participants to explore the site on their own, so it is not sure whether they were engaging in the site or just logging in and out of the site. Second, they only collected the timestamp of each of the logins of the participants, which they will overcome by collecting the timestamp of every user action. Third, they logged out participants after each 10-minute period of inactiveness, for which there is an error of ±10 min while calculating the total time spent on the site. Fourth, they collected the user device, browser and operating system information through Google Analytics, for which they could not tie it to individual users. Fifth, they correlated two measures of engagement, which would be correlated anyway. Sixth, the study participants were extremely incentivized, which might have increased the engagement level. Finally, the study did not have a strong theoretic background and used a very small sample size. The study in this dissertation largely follows the above study but focuses on overcoming its limitations. 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 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.

2.5 Theoretical Frameworks

Two theoretical perspectives are relevant in the context of this research are discussed below:

2.5.1 Situative theory

In order to design the learning task based on the OWLS, the situative perspective of learning is used. According to the situative perspective, an individual's learning is affected by the social and the material context (Johri & Olds, 2011; Newstetter & Svinicki, 2014). Considering the material context, learning is mediated by tools and artifacts, so "the role and use of tools is important to understand" (Johri & Olds, 2011, p. 160). For example, learning may differ if the OWLS is used instead of a theoretical textbook for teaching environmental monitoring concepts. Thus, it is important to investigate students' engagement with such tools or artifacts like the OWLS and also to find out the way it is being used by students, which affects their learning.

The situative perspective further highlights that individuals fully participate in activities if they understand that these activities lead to accomplishing a larger goal, such as learning to become a member of the engineering community (Johri & Olds, 2011). Cyberlearning systems, including remote labs, virtual labs, online hybrid labs and augmented reality labs have gained popularity as tools that can engage students to participate in important engineering activities like problem-solving, modeling and experimentation (Madhvan et al., 2010; Henke et al., 2013). Specifically, cyberlearning systems, like the OWLS and the HydroViz, utilize digital technologies to remotely situate users at field sites (Habib et al., 2012; Delgoshaei, 2012; Delgoshaei and Lohani, 2014; Brogan et al., 2014; Brogan et al. 2016). The learning happening through the OWLS can be contextualized with the situative perspective of learning as it is a tool that can be used to engage students to participate in activities with a larger goal of helping them to become a part of the engineering and science community concerned with environmental monitoring education. In this study, the OWLS-based task will be designed to help students learn to solve real-world environmental problems by monitoring their local Webb Branch watershed, which fulfills their course learning objectives.

Situative perspective of learning also emphasizes for “creating learning environment that allows learners to chart their own learning path”(Newstetter & Svinicki, 2014, p. 13). Similarly, the OWLS is such a guided learning environment that allows individual students to navigate the content in their own ways and progress at their own pace to monitor the remote environment and solve related problems. The students’ specific learning paths will be recorded with the user-tracking system for analyzing the variation in student engagement within the OWLS.

2.5.2 Engagement Theory

For understanding and measuring the variation in the engagement of the students within the OWLS, theories related to engagement were explored. The literature on engagement is diverse and each researcher had explained it in various dimensions. Stark & Lattuca (1997) explained it by bringing in Pace’s (1998) idea of students’ involvement with his/her academic environment, and Austin’s (1993) definition of students’ interaction with the learning environment. Both of these notions of engagement distinguishes it from the concept of motivation (psychological state) and related it a behavioral feature of a student. Similarly, according to Kuh (2009) the term engagement encompasses constructs such "as quality of effort and involvement in productive learning activities" (p. 6). Fredricks, Blumenfeld & Paris (2004) highlighted that engagement can be viewed as a "meta" construct that encompasses three aspects of engagement: behavioral, emotional and cognitive. 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. Boekaerts (2016) in his commentary on the contribution of six studies related to classroom engagement summarized that engagement is a multidimensional construct that is malleable and context-specific. Engagement results from *how an individual feel, think and behave within a specific context* and is reactive to the changes in the learning environment (Connell, 1990 in Fredricks, Blumenfeld & Paris, 2009).

Engagement mediates the impact due the changes in the learning environmental 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 (Boekaerts, 2016). Overall, prior researches on engagement have shown that engagement is related to positive undergraduate academic achievement, student drop-out rates, student retention, student motivation, students' self-regulation and institutional success (Beer, Clark, & Jones; 2010). Furthermore, engagement have been investigated within various learning contexts, such as engagement within an authentic task, a course, a degree program, a school community, learning resources and even a computer-mediated technologies. In this research, the focus is to understand the variation in engagement and its relation to learning within the OWLS. Therefore, in the next paragraph, the concept of engagement will be explained in terms of human-computer interaction (HCI).

2.5.2.1 Engagement within Cyberlearning Systems

Within the context of HCI, engagement is defined as the human response to computer-mediated interactive systems (O'Brien & Cairns, 2016). For computer-mediated interactive tools like the OWLS, the aim is not only to facilitate engaging user experience with the system, but for users to behave in certain ways so that they have positive learning outcome utilizing the system (Wiebe & Sharek in O'Brien & Cairns, 2016). In other words, the goal is not to increase the number of clicks on resources or to play a video frequently within the OWLS, but the purpose is to engage users to invest time and effort in experiencing the system so that they can learn and develop skills utilizing it. The behavior exhibited by an individual within a cyberlearning system is an indicator for the level of engagement and the engagement process that leads to learning. This entails to not only investigate what has been learned but also to know the engagement process. O'Brien & Toms (2008) have proposed a process model for engagement that considers engagement as a four stages process and a product of interaction. The four stages include point of engagement, engagement, disengagement and re-engagement as shown in figure 2-1. The *attributes of engagement*, which are the characteristics of user-computer interaction that impacts or is a factor of engagement, are also included in the figure 2-1. For example, the engagement is initiated if the users find the system aesthetically appealing, interesting and if it meets their learning goals. The users can sustain their engagement if they get positive effect by interacting with the system or are appropriately challenged. Disengagement can happen if a system is not user friendly or provides negative effect or system usage is affected by external factors like time constraint. Re-engagement is when users come back to use the system again if they find it interesting or rewarding. It is also mentioned that the intensity of the attributes may change over the course of interaction. This model was verified through an exploratory study that involved interviewing video gamers, online shoppers, web searchers and e-learners. Some of these attributes of engagement, such as aesthetic, usability, sensory appeal are related to the usability variables of efficiency, effectiveness and satisfaction with a system. This demonstrates that the concept of engagement encompasses the concept of usability, which is important for utilizing a cyberlearning system for learning, and also focuses on users' thoughts, feelings and degree of activity during system use.

However, it is more essential for cyberlearning systems to exceed usability and provide users with an engaging experience (O'Brien & Toms, 2010). The model of engagement provided by O'Brien & Toms (2008) provides a complete picture of the process of engagement of a user with interactive applications. For the current study, this model of user engagement will help in explaining the students' engagement within the OWLS.

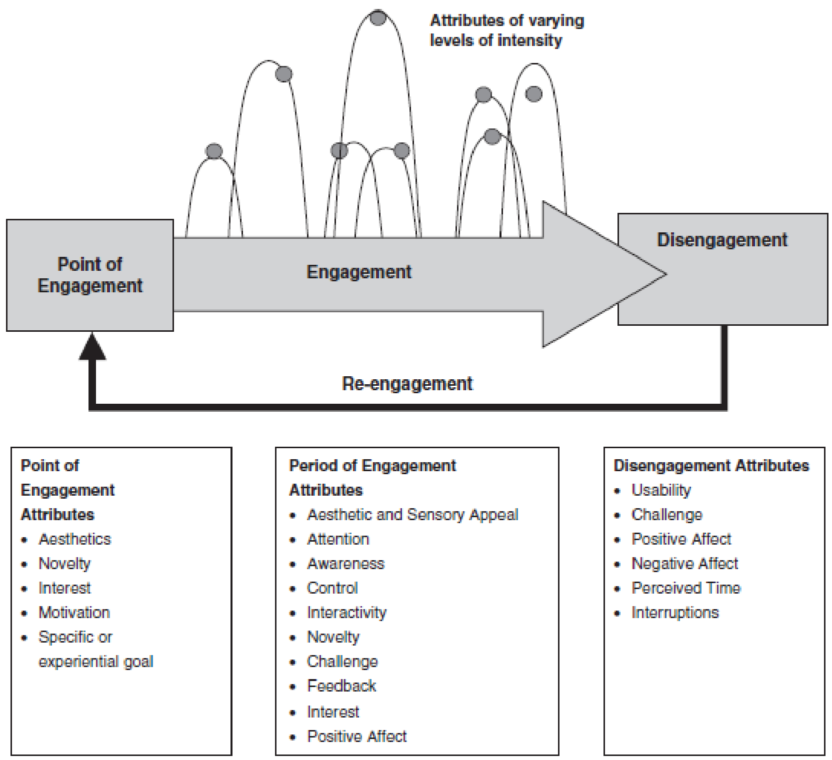


Figure 2-1. Process model of user engagement and its attributes (O'Brien et al., 2008)

2.5.2.2 Measurement of the Engagement within Cyberlearning Systems

There are various ways in which engagement has been measured in literature: self-reports behavioral measurement and psychological measurement (O'Brien & Cairns, 2016). Self-reports can provide data on how students perceive their engagement in a learning task using a cyberlearning system. It can ask each learner to report on various attributes of engagement, taking context and individual differences into account. Self- reports can be collected during the task or after a learning task has been completed. Collection of self-reports during a task, interrupts students' engagement process, while collecting self-reports long after a learning task also limit the reliability of the data collected. For these reasons, it is suggested to administer post hoc self-reports immediately after a student completes a certain task related to which engagement question will be asked. Several self-report scales have been developed in literature to measure engagement of an individual student in various contexts (Kuh, 2009), but many of these scales do not have established validity and reliability (O'Brien and Toms, 2013). One choice for a scale is the User Engagement Scale (UES) developed by O'Brien & Toms (2010) that measure user engagement with computer-mediated interactive systems and contains sub-scales based on the various attributes of engagement identified in their process model of engagement (O'Brien & Toms, 2008). Another way of measuring engagement is to evaluate students' behaviors while conducting a learning task. For traditional classrooms, behavioral engagement has also been measured in various ways, such as class attendance and time on task (Douglas & Alemanne, 2007; Kuh, 2009). For cyberlearning systems, there is potential to collect real-time user-system interactions with timestamp that can provide insight to the behavioral pattern of engagement of the students. In this case, students' total number of clicks or their time on task within the system can be a measure for behavioral engagement (Beer, Clark, & Jones; 2010). Another way to measure engagement is to use physiological measures. These can be measured remotely using camera and image processing tools that captures facial expressions, track eye movements and body postures. Direct physiological measurements include application of sensors on the students' bodies to capture their heart rate, brain activity and electrodermal data (Hardy, Wiebe, Grafsgaard, Boyer & Lester, 2013).

2.5.2.3 Measurement of the Engagement in this Study

In this current study, to understand the engagement process, self-reports and behavioral measures was be collected. The behavior/interactivity of the users within a cyberlearning system was collected by tracking users' action within the system, while self-reports was collected to understand the attributes of engagement that influences such interaction. To track individual users with a cyberlearning system, the development of a user-tracking system is described in the next chapter. While, the User Engagement

Scale (UES) that will be employed to collect self-reports on their level of engagement, is described below. Both these data can be related to develop a holistic view of the variation in engagement of individual users within the cyberlearning system, which will then be investigated for its impact on learning. This analysis has implications for both improving students' learning and engagement within the OWLS as well as for taking OWLS-related design decisions.

2.5.2.4 User Engagement Scale

The user engagement scale (UES), developed by O'Brien and Toms (2010) by reviewing and combining attributes from the following: a) existing literature on flow theory, aesthetic theory, play theory, and information interaction theory (O'Brien & Toms, 2008), b) existing questionnaires exploring engagement with educational multimedia systems (O'Brien and Toms, 2013) and c) their prior exploratory study conducted with video gamers, online shoppers, web searchers and e-learners (O'Brien & Toms, 2008) where they proposed the model of user engagement process (figure 2-1). Thus, the attributes of engagement contained in the UES are comprehensive than previous measures and expand the scope of measuring engagement than the ones employed in the past. UES considers engagement as a multidimensional construct with the following attributes of engagement: aesthetic appeal, endurability, felt involvement, focused attention, novelty and perceived usability (O'Brien and Toms, 2010).

- *Aesthetic* appeal deals with users' opinion about the visual appearance of a computer application interface.
- *Endurability* deals with users' overall assessment of their experience using the computer application including their perceived success using the system, their likelihood to return and recommend to others about the system.
- *Felt involvement* consists of users' feeling of being interested and drawn-in by the computer application.

- *Focused attention* contains elements of flow, especially focused concentration, immersion and temporal detachment from surroundings.
- *Novelty* includes users' level of interests in the task and curiosity induced by the system and its resources.
- *Perceived usability* combines users' emotional and cognitive response to the system.

The UES has been administered widely with users of a variety of computer applications, such as interactive search systems, online shopping, webcast, social network environments (facebook), online news, video games and even educational applications (O'Brien and Toms, 2013; O'Brien & Cairns, 2016). Similar to the final study, two researchers employed UES in the educational domain to investigate user engagement with learning tools and to relate it with learning outcome. Whitman (2013) found that tutorials that are interactive in nature engage students more than baseline tutorials, although the learning outcome is similar in both the applications. Vail et al. (2015 in O'Brien & Cairns, 2016) showed that students had more learning gain with human tutors than interactive tutorial, although the later was more engaging. Again, between baseline tutorial and an interactive tutorial, the later was more engaging, but the learning gain was similar. These two studies showed that learning gain does not always equate with engagement in all contexts. These results emphasize the complexity of various learning environments where contextual factors, like students motivation and ability to learn, may also affect learning outcome (Calder, Malthouse & Schaedel, 2009). Hence, more research on understanding engagement and learning in different educational contexts is essential for comparing engagement process across educational applications.

In respect to reliability and validity of the instrument, three of the sub-scales of the UES (perceived, usability, focused attention, aesthetic appeal) have shown stability in retaining items across 5 implementation with 4 types of application (e-shopping, facebook, webcast and wikiSearch), while the others three sub-scales have varied between applications. Among the five implementations, one study showed six distinct sub-scales, three studies revealed the three sub-scales (mentioned above) and combined rest of the items to form one sub-scale, while the fifth study showed five sub-scales and eliminated the sixth sub-scale. Due to this variability, it is recommended to use the full 31-item UES instrument adapted to a specific application and to test it in various learning environments and under different circumstances. Analyzing the results will help in determining the attributes that are most salient to user engagement in that learning environment (O'Brien and Toms, 2013).

2.6 Summary

In summary, this current study aims to extend the research going on in the domain of educational data mining and learning analytics by investigating personalized learning and engagement within the context of a cyberlearning system, the OWLS. Compared to the different types of cyberlearning systems the OWLS combines features of both remote and virtual labs to engage students for environmental monitoring education. The addition of data visualization features of the OWLS will increase the flexibility and usability of the system for environmental monitoring. Additionally, drawing ideas from past studies that utilized user-tracking data to gain insights about learning process, this study aims to develop a custom-user tracking system for exploring individualized engagement and learning within the OWLS for environmental monitoring education. The study intends to step beyond the question of whether OWLS helps in learning, in addition investigates how students use the tool to learn and complete an OWLS-based task, which has not been investigated earlier. The advancement of the OWLS with a user tracking system also focuses to increase the research potential of the OWL in the context of personalized learning. By presenting the computational architecture and functionalities of the secure individualized user-tracking system of the OWLS, this study aims to inform literature about the distinctive technologies that often creates barrier for implementing technologies in educational settings (Liu, Calvo, Pardo & Martin, 2015). Unlike, many studies that dealt with user-tracking data, this study utilizes situative theory and engagement theory to design and explore the variation in engagement and learning, and its relationship in the context of the OWLS employed as a cyberlearning tool within a classroom environment (blended classroom). Compared to the reviewed studies, this current research investigates at individual level, students' conceptual learning outcome, perceived learning, behavioral engagement, perceived engagement, and their perception towards the learning value of the various components of the OWLS, which allows a holistic understanding of students' experiences with the OWLS. According to the author's knowledge, none of the previous studies have investigated into individualized engagement and learning, and its relationship for a specific learning task within a classroom environment using this particular combination of variables. Further, in this study, individual student's variation in engagement is explored in terms of their inherent features, like gender, and background knowledge, which have been rarely studied in the literature with user-tracking data, although they are known to be important characteristics to be considered in studies related to student learning and engagement (Stark & Lattuca,1997; Pardo, Han & Ellis, 2017; Fredricks, Hofkens, Wang, Mortenson & Scott, 2018). Finally, various common analytical methods from the domain of EDM and LA, such as statistical techniques, visual analytics and data mining techniques are applied in this research. The purpose of this study is not intended to generalize to a bigger population but to inform researchers and practitioners about students' learning and engagement within a classroom environment utilizing a cyberlearning system, like the OWLS.

Chapter 3: Advancement of the OWLS

The advancement of the OWLS includes the addition of the following components: 1) user tracking system with login functionalities, and 2) data availability and visualization features. The key terminologies for this chapter will be explained in section 3.1. In section 3.2, the four stages of the Learning Enhanced Watershed Assessment System (LEWAS) are presented to highlight the stages in which the development is performed. In section 3.3, the communication processes involved between the LEWAS server and its clients along with the role of the programming languages used for the development are discussed. The user tracking system is described in section 3.4. Finally, the data availability and visualization features are explained in section 3.5.

3.1 Key Terminologies

Web servers: Web servers are computers that run specific software (e.g., Apache) to process, store and deliver website components/files (e.g., HTML files, CSS style sheets, JavaScript files) to the users' computers over the internet. It also manages network traffics (Mozilla Developer Network, 2016).

Clients: These are machines, such as a laptop, desktop, tablet, mobile phones, etc., where users can run an application/software (e.g., OWLS) on web browsers (e.g., Chrome, Firefox) (Mozilla Developer Network, 2016).

HTTP: It is called the hypertext transfer protocol used for transmitting website components/files (e.g., HTML files) between a server and a client. It is a stateless protocol, which means it treats each request-response pair between a server and a client as a HTTP transaction, and treats each transaction separately (MDN Web Docs, 2018).

Web application: It is computer software that is stored on a web server and transmitted over the internet to be viewed on a browser. It uses the client's browser to run various functions. The OWLS is a web application (Techopedia .com, 2018).

Database: It is a collection of information or data stored on a computer that is structured in a way that helps in accessing, managing and updating it (Britannica, 2018). The data can be in various formats, such as number, letters or words. A relational database is a type of database where data are stored in tables and it allows detecting and accessing a particular data in relation to another data in the same database. It is usually stored in a web server (WhatIs .com, 2018).

Application Programming Interface (API): As the name implies, it is a software or program acting as a middle way to allow smooth communication between two applications (MuleSoft , 2018). For example, when a weather application (app) is opened on the mobile phone, an API connects the app to the internet, receives data (the location information) from the application, and sends it to the server. The server retrieves the data, interprets it, performs some function and sends back weather data related to the location. The API receives the data and presents on the app in a readable format.

3.2 LEWAS Stages

The LEWAS has the following four stages: 1) instruments that are used for environmental monitoring including an acoustic Doppler current profiler, a water quality sonde and a weather station taking measurements every 1-3 min., 2) data-processing occurring locally on a Raspberry Pi, 3) data storage on a remote LEWAS database within a web server, and 4) end user interfaces (local and remote), which enable users to access LEWAS data, e.g., the OWLS (http://owls.lewas.ictas.vt.edu) for research and education (Figure 3-1) (Basu et. al., 2015; Brogan et al, 2016). The LEWAS has been designed as a flexible and expandable environmental monitoring system that can easily be adapted and deployed in a wide variety of settings (such as a similar system had been set-up at the University of Queensland). The advancements impacted the third and the fourth stages described above.

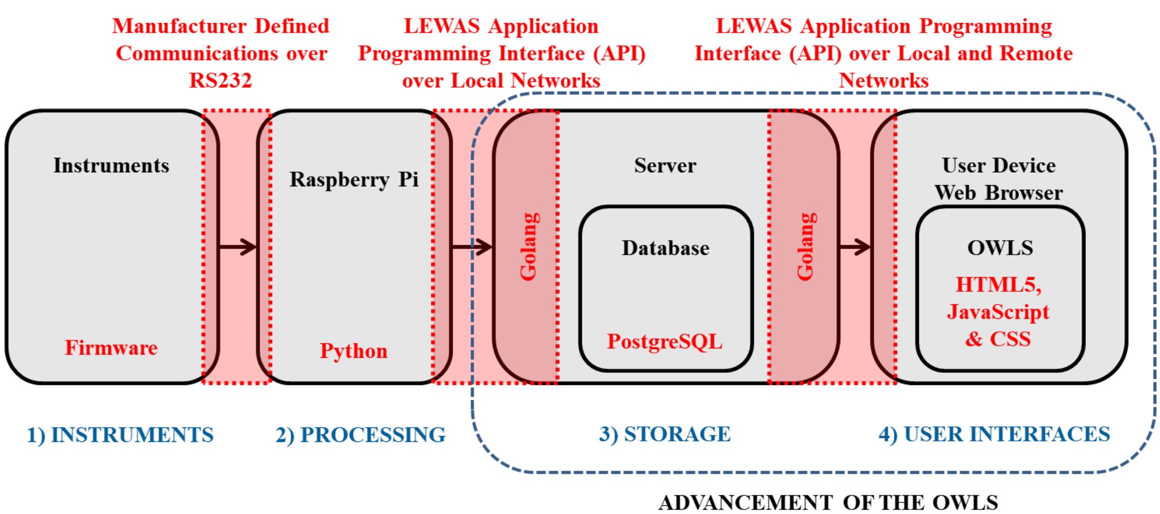


Figure 3-1. LEWAS stages.

3.3 Communication Processes between the Third and Fourth Stages of the LEWAS

Following sections describe the communication process between the third and fourth stages, for which the following are discussed: 1) the client-server architecture, 2) the OWLS web application, and 3) the communication process through LEWAS Application Program Interface (API).

The client-server architecture. The network architecture between the end users' interface (stage four) and the LEWAS web server or LEWAS server (Stage three) follows the *client-server architecture*.

The *LEWAS web server* is located in the LEWAS lab. Web servers are connected to the internet and are accessible by a domain name (e.g., LEWAS web server is accessible via lewas.ictas.vt.edu). For the communication between a server and its clients- clients can request web resources (e.g., HTML files, data, images) from a centralized web server. The server has software that recognizes the request and sends back a response to each client with the web resource it requested. The client-server architecture of LEWAS is shown in Figure 3-2. The communication through the request/response loop follows a protocol (set of rules), which, in this case is HTTP and understood by both the web server and the client.

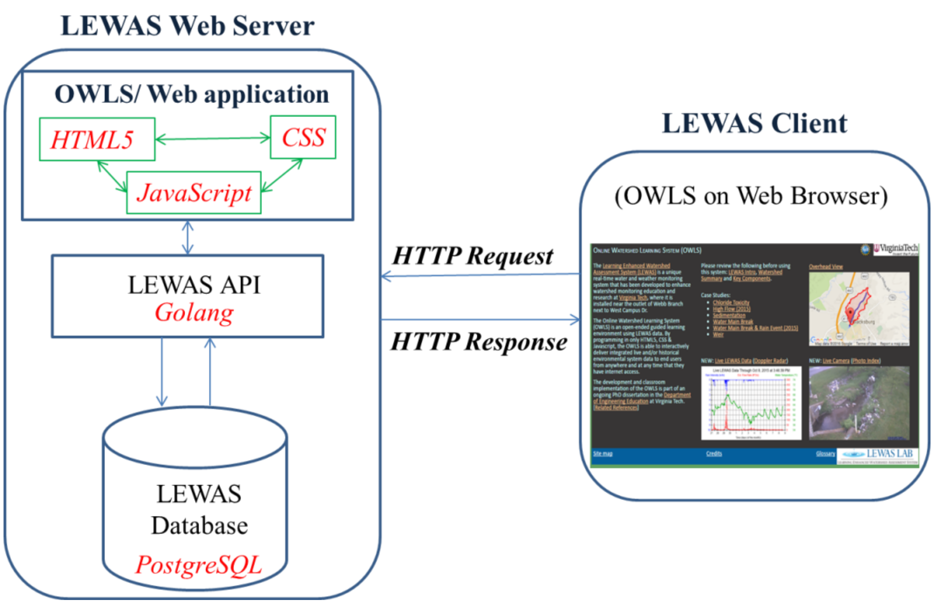


Figure 3-2. Client-server architecture of the LEWAS

OWLS web application. The OWLS is a static web application that is stored in the LEWAS web server and is made up of many HTML files, which uses CSS file/s and JavaScript file/s. The OWLS is accessible over the internet through a web browser running on the client-side. The OWLS also includes various image and video files, which is embedded in an HTML file. In order to achieve the desired platform independence, the version of HTML used here is the HTML5. All these three languages, HTML5, CSS and JavaScript, are also widely supported across platforms like laptops, tablets, mobile phones, etc. *HTML* is a markup language and one of its new versions is HTML5. HTML5 has many new elements, attributes, and behaviors. Overall, it is used to define the user interface structure and to present content in a way that all web browsers on all types of devices can understand. For, example it defines the position of the buttons, drop-down menus, text contents, images, and data in a web browser. Different HTML pages define the different web pages of a web application. *Cascading Style Sheet (CSS)* is a stylesheet language, used to format/style or describe the presentation of a document written in HTML or XML. For example, it can define the color, size, shape of a button, and the background color of a HTML page. It can be just one CSS file that defines the styles of all the HTML objects in a web application. This CSS file can be imported to all the HTML pages (Mozilla Developer Network, 2016). *JavaScript* is a scripting language used to add interactive features on web pages. It is a lightweight, interpreted and object-oriented language. It also supports procedural/functional programming style. It runs on the client-side of a web application. JavaScript is used to define the functionality/behavior of the interactive events on an HTML page. For example, JavaScript is used to define the action of a button when it is clicked. This is written as a JavaScript function. All the JavaScript functions for a web application can be written in one ".js" file that can be imported to all HTML files (Mozilla Developer Network, 2016).

Communication through LEWAS API. The OWLS web application consists of various static HTML pages including the single_graph.html and camera.html that present the real-time LEWAS environmental data and the live feed of the camera from the remote LEWAS field site to the clients, respectively. These LEWAS environmental data and video (every 15 min of camera feed converted to a compressed video in WebM format) are stored in the LEWAS database and a video archive, respectively, which are in the LEWAS server. The LEWAS database is a PostgreSQL database. It is a powerful, open-source and object-relational database system that run on several operating systems, such as Linus, UNIX and Windows. It has several database tables that store the data from the LEWAS instruments and also the metadata (data about data). There is also a LEWAS application programming interface (API) on the LEWAS web server, which are programs written in Golang programming language. It acts as a uniform interface between the OWLS and the LEWAS database and helps in communication between them to fetch the data (Figure 3-2). This separation helps in abstracting the details about the data storage from the web application/OWLS and thus the complex data structure remains internal to the server. This improves the portability of web OWLS and its enhancement can be done independently. However, JavaScript functions needs to be written for OWLS that corresponds to the API functionalities and video archive, so that LEWAS data and live video can be fetched efficiently. Now, if an OWLS client/user requests to access the data in the single_graph.html page, the corresponding JavaScript function triggers the request to the LEWAS API, which extracts data from the LEWAS database and then sends a JSON object back appended with the HTTP response. JSON is a JavaScript object notation format, which helps in exchange of data over the network, and it is contained as an attribute-value pair/s. The JavaScript then reads data from the JSON object, and shows it to the client in the form of data points on the graph.

3.4 User Tracking System

The user tracking system involves two sub-processes: 1) implementing a login system to identify individual users, and 2) adding the tracking functionalities for identifying each user's navigations and actions within the OWLS. A web-application framework, called the Express, based on the Node.js programming language, is used for developing the system. A PostgreSQL database called "owlsusers" is used to store user's sign-up and user-tracking information, which is a separate database than the LEWAS database. An overview of how the user-tracking system is implemented is discussed in the following sections.

3.4.1 Node.js and Express framework

Node.js is an open-source, cross-platform, free runtime environment used by worldwide developers to create various kinds of server-side applications in JavaScript (W3schools .com., 2018). It is utilized for running codes outside the browser, for which, it supports traditional operating system APIs including HTTP and file system libraries. It is designed to optimize throughput and scalability that makes it suitable for real-time web applications, such as the user tracking system. The node package manager (NPM) provides huge number of reusable libraries, some of which has been used to support various functionalities in the user tracking system, such as bcrypt-nodejs, passport, HTTP and pg-hstore. For instance, the HTTP package can be used to create a local server that can listen to a request from a browser and respond to it.

Express is the most prevalent, fast, minimalist web framework for Node.js (Expressjs.com., 2018) that contains underlying libraries of other popular Node.js web frameworks. As shown in figure 3-3, Express provides methods to indicate the function that should run for a specific HTTP request type (GET, POST, SET, etc.) and URL pattern (“Route”). It also provides methods to specify the use of a particular template (“view”) engine, its location and which one to render as a response, as shown in figure 3-3. Express supports addition of functions (“middleware”) within request handling pipeline. It has many middleware packages (Docs.npmjs .com., 2018) that manage many web development functionalities, such as middleware for handling cookies, sessions, users-logins and also to receive GET/POST parameters. It is compatible to any database mechanism that is supported by Node.js (Docs.npmjs.com., 2018).

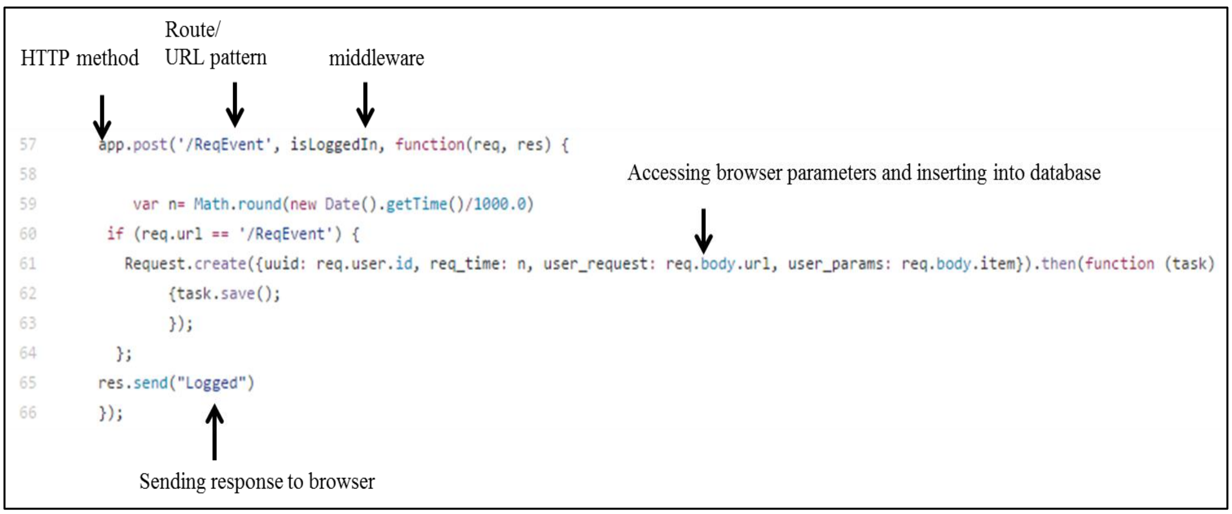


Figure 3-3. A code snippet from the user tracking system to show an example of a request handling mechanism written using the Node.js-based Express framework.

3.4.2 Client-side of the User Tracking System

A new client can access the OWLS by typing the following URL: http://owls.lewas.ictas.vt.edu on their browser. The client will be taken to the login page with a “Signup” button. For new clients, they have to click the “Signup” to go to the signup HTML page. Here, clients need to enter their, first name, last name, email id, and their password, and click the ‘Signup’ button. Once, a client sign up, the client’s information is stored in a PostgreSQL database along with a user id that is generated to uniquely identify the client across the OWLS web pages and devices. After this process, the client becomes the authorized user of the OWLS. The process of giving privilege to the client to access the OWLS resources is called authorization. From this time onwards, to access the OWLS, the clients need to provide their already authorized email address and password within the login.html page. These email and password are compared against their information stored in the database. If the information matches, the client is given access to the OWLS. This process of checking the eligibility of a client for getting access to certain resources is known as authentication. The above mentioned processes are visually represented in figure 3-4. These signup.html and login.html pages are written in Embedded JavaScirpt (EJS), which is a templating language used to dynamically generate HTML pages with plain JavaScript. The authentication and authorization functions will be explained in the next section.

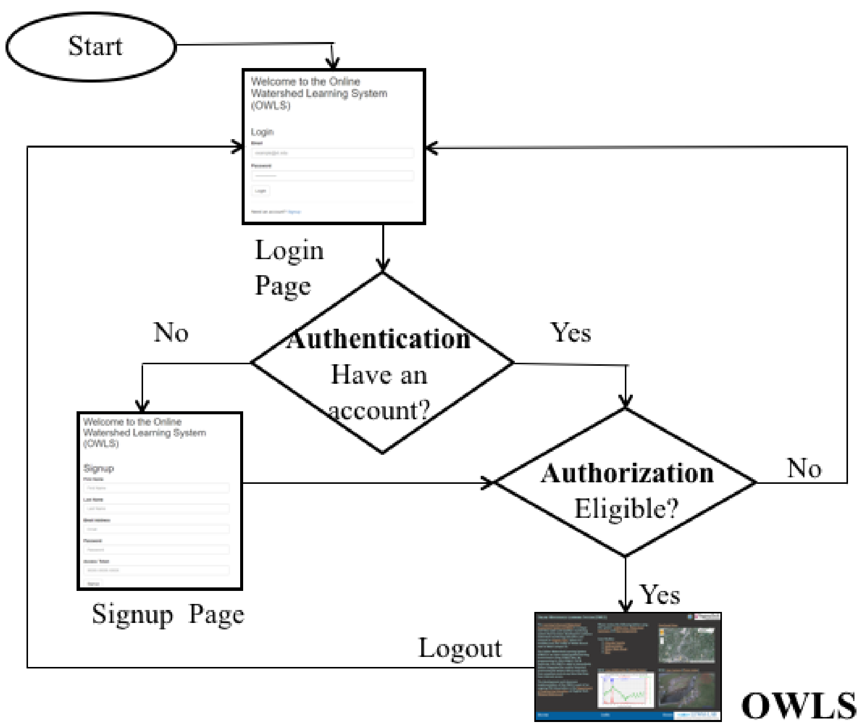


Figure 3-4. Client-side processes of the user tracking system

3.4.3 Server-side of the User Tracking System

The user tracking system follows a Model, View, Controller (MVC) software architecture. Model constitutes the JavaScript files that define the data structures of the database tables and methods to interact with the database. View contains the files that the users interact with on their browsers. Controller in this case, is the program that takes in users' requests from the views, extract data from the requests, maps into the models to store it in the database. In this user tracking system, the user.js and user_req.js files are the models, which map the user signin information and the other user tracking information (detailed below), respectively, to store in the corresponding database tables. View constitutes files that create the HTML files shown in figure 3-4. The route.js acts as the main controller function that utilizes app.js to receive the HTTP requests (using GET/POST method) from the users and provide the appropriate response. The app.js is the main configuration file for the express-based user tracking system. It imports (requires) several Node.js modules that are useful for this application. Some of the important functionalities implemented within the route.js files are as follows:

Authenticating and authorizing a user. As clients send request from the signup.html page or the login.html page with their information, the route .js communicates with the passport.js file that utilizes passport module with its local-login strategy to create a new user record and save it in the database, or to authenticate the already existing user. The code snippet from route.js calling the authentication function when a user sends request from login.html page is shown in figure 3-5.

```
//Authenticating a user
app.post('/login', passport.authenticate('local-login', {
    successRedirect: '/index.html', // redirect to the secure profile section
    failureRedirect: '/login', // redirect back to the signup page if there is an error
    failureFlash: true, // allow flash messages
    badRequestMessage: 'Please enter your account credentials to login.'

} ));
```

Figure 3-5. Node.js Script for Authentication

***Retrieving a user's page request and browser information*.** As a user logs in to the OWLS, he/she navigates from one webpage to the other. As they click on a link within the OWLS to move to a different webpage, a request string is generated that contains their unique user id and their requested URL. The request header contains a user agent (ua) section that is parsed using a ua-parser module to extract the operating system, browser and device information of the user. This ua information is useful to detect individual user across devices and to check if the user tracking system is compatible with various operating systems, browsers and devices. All these information from the request string along with the timestamp of the request are stored in the database. The code snippet from route.js that defines the functionality described above is shown in figure 3-6

```
// Route middleware to retrieve user's webpage request and device information
function logRequest(req, res, next) {
        var userAgent = req.headers['user-agent'];
        var browser= uap.parseUA(userAgent).toString();
        var os= uap.parseOS(userAgent).toString();
        var device=uap.parseDevice(userAgent).toString();

        var n= Math.round(new Date().getTime()/1000.0)//current epoch time from https://www.epochconverter.com/

        if ((req.url.includes('.html') && !req.url.includes('?'))|| !req.url.includes('.')) {
            Request.create({uuid: req.user.id, req_time: n, user_request: req.url, user_browser: browser, user_os:os,
            user_device:device}).then(function (task)
            {task.save(); //req_time: new Date()
            });
        }
    next();
}
```

Figure 3-6. Node.js Script for retrieving a user’s page request and browser information.

Retrieving user’s action information within a webpage. In many of the OWLS web pages, users have the option to click on various objects, such as click to play the YouTube video within the caseStudy_highFlow2015_09.html. To retrieve all these click events, a JavaScript method is written in all these OWLS web pages (client-side) that captures the information of the object that has been clicked and its corresponding name of the webpage. As a click event occurs, the method triggers a server-side request with “/ReqEvent” URL and POST method. The router.js recognizes the request URL and extracts the clink event information along with the timestamp to store it in the database. The code snippet from route.js that defines retrieve the information is shown in figure 3-7.

```
//Retriving user's action information within a webpage
app.post('/ReqEvent', isLoggedIn, function(req, res) {

    var n= Math.round(new Date().getTime()/1000.0)
    if (req.url == '/ReqEvent') {
            Request.create({uuid: req.user.id, req_time: n, user_request: req.body.url,
            user_params: req.body.item}).then(function (task)
             {task.save();
                        });
        };
    res.send("Logged");

});
```

Figure 3-7. Node.js Script for retrieving a user's action information within web pages

Retrieving users' location information. The OWLS is accessible from anywhere across the globe. To capture users' location information (latitude and longitude), a JavaScript method is written on each of the OWLS web pages that run with the page load event. This method triggers a request with "/Reqlocation" URL and POST method and passes the user's latitude and longitude information to the server. The router.js recognizes the request URL, extract the location information and store it in the database. The code snippet from route.js that defines the functionality described above is shown in figure 3-8.

```
//Retriving user's location information
app.post('/Reqlocation', isLoggedIn, function(req, res) {

    var n= Math.round(new Date().getTime()/1000.0)
   if (req.url == '/Reqlocation') {
        Request.create({uuid: req.user.id, req_time:n, user_request: req.url, user_latitude: req.body.latitude,
        user_longitude:req.body.longitude}).then(function (task)
         {task.save();
                  });
        };
       res.send("Logged")
});
```

Figure 3-8. Node.js Script for retrieving a user's location information.

Retrieving users' browser status. When a user accesses the OWLS in one browser, simultaneous the user can open up several other browsers or screens on their device. To check if the user is active on the OWLS browser, a method is written in JavaScript and embedded within all the OWLS web pages. This method runs every minute and triggers a server request with "/ReqBrowser" URL and POST method and passes the name of the OWLS webpage with the current browser status (active/inactive). The router.js recognizes the request URL, extract the webpage name and browser status information and stores it in the database along with the timestamp. Later, this information is utilized to calculate the total time a user was on the OWLS browser. The code snippet from route.js that defines the functionality described above is shown in figure 3-9.

```
//Retriving user's browser status
app.post('/ReqBrowser', isLoggedIn, function(req, res) {

   var n= Math.round(new Date().getTime()/1000.0)

if (req.url == '/ReqBrowser') {
  Request.create({uuid: req.user.id, req_time: n, user_request: req.body.url,
  user_params: req.body.userStatus}).then(function (task)
       {task.save();
       });
 };
res.send("Logged")
});
```

Figure 3-9. Node.js Script for retrieving a user's browser status.

Database of the user tracking system. As mentioned before, the user tracking system stores information in a database, called the "owlsusers" written in PostgreSQL. This database is chosen to be consistent with the LEWAS system that uses a similar PostgreSQL database to store its environmental data (mentioned earlier). Two tables, "users" and "requests" are created dynamically by the models (if it did not exist in the database) to store users' signup information and tracking data, respectively, into the database. The database was created to securely store clients' information and use it for analysis. Figures 3-10 and 3-11 show the column names and data types for each of these database tables, respectively.

```
                  Table "public.users"
  Column   |           Type           | Modifiers
-----------+--------------------------+-----------
 id        | uuid                     | not null
 email     | character varying(255)   |
 password  | character varying(255)   |
 firstname | character varying(255)   |
 lastname  | character varying(255)   |
 privilege | integer                  |
 createdAt | timestamp with time zone | not null
 updatedAt | timestamp with time zone | not null
Indexes:
    "users_pkey" PRIMARY KEY, btree (id)
```

Figure 3-10. The “user” table storing each users’ signup information

```
                                        Table "public.requests"
     Column     |           Type           |                          Modifiers
----------------+--------------------------+-------------------------------------------------------
 id             | integer                  | not null default nextval('requests_id_seq'::regclass)
 uuid           | character varying(255)   |
 req_time       | integer                  |
 user_request   | character varying(255)   |
 user_params    | character varying(255)   |
 user_browser   | character varying(255)   |
 user_os        | character varying(255)   |
 user_device    | character varying(255)   |
 user_latitude  | character varying(255)   |
 user_longitude | character varying(255)   |
 createdAt      | timestamp with time zone | not null
 updatedAt      | timestamp with time zone | not null
Indexes:
    "requests_pkey" PRIMARY KEY, btree (id)
```

Figure 3-11. The “user” table storing each users-tracking data

3.4.4 System Developmental Steps

Development of the user tracking system was challenging as it constitutes several steps to get to the desired system with required functionalities. First, the Node.js and Express framework were explored to understand its use and implementation, and to realize its suitability to the user tracking system. Second, several discussions during the development were carried out within the LEWAS team to understand the requirements of the system. Third, several developmental iterations and searches were performed to find suitable modules/libraries, and to implement it in ways that would meet the requirements of the system. Fourth, each functionality of the system was developed and tested out separately before they were integrated to the full system. Fifth, the current database design is a product of critical analysis of the types and format of data essential for future analysis that would produces desired outcomes in this research study and decrease the data pre-processing time. Finally, the system had to be tested out multiple times within the development and production server/environment before its actual implementation. During phase 4, the user-tracking system was updated with functionalities that can track users' actions within the newly developed data availability and visualization features.

3.5 Data Visualization and Availability Features

Data availability and visualization features were added to enhance the interactivity of the earlier version of the OWLS. The components of the earlier version of the OWLS have been listed in Table 1-1 that includes two webpage called single_graph.html and rawData.html. Specifically, both these page of the OWLS was recoded to make the code simpler and to add the data availability and visualization features. In this section, first the technology employed to add the data availability and visualization components of the OWLS are discussed, and next, the specific features that were added are presented.

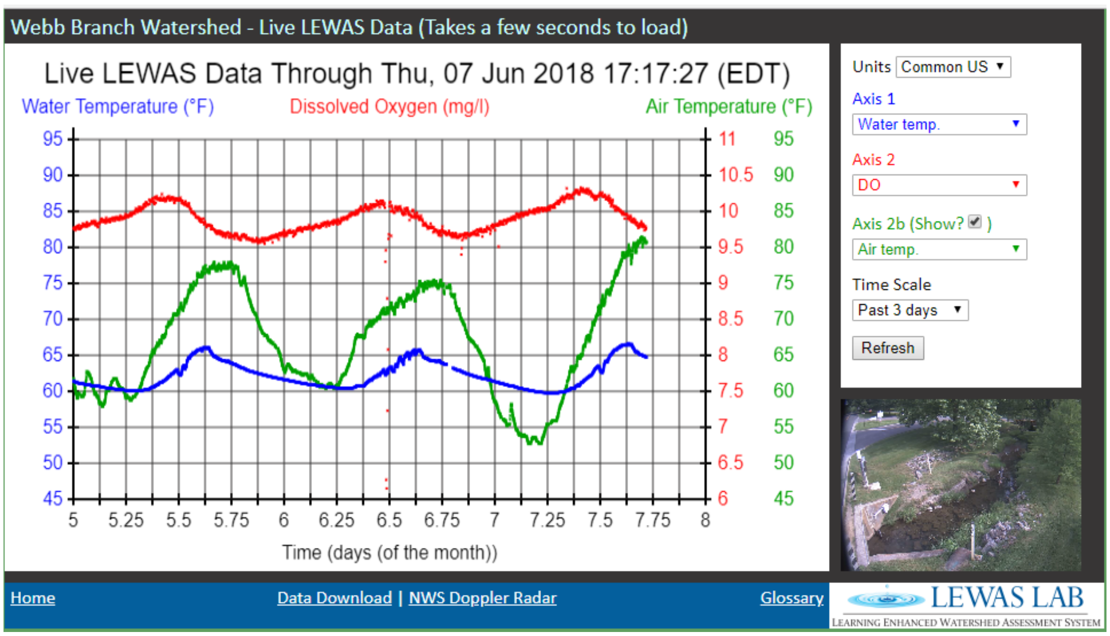
3.5.1 Data-Driven Documents (D3)

Data-Driven Documents (D3) is a library of JavaScript which aids in adding data visualization and interactive features to graphical displays. It is extremely fast and able to handle large datasets and dynamic behaviors for interaction. D3 works with HTML5 (Hyper Text Markup Language 5), CSS (Cascading Style Sheets), and SVG (Scalable Vector Graphics) to create various types of graphs (Bostock, Ogievetsky & Heer, 2011). The addition of SVG provides more complex visualization methods which are aesthetically pleasing. As D3 works with HTML5 and CSS, it was easy to include it in current code without too much of a transition. All D3 requires to run is a quick download and a line of code within the head of an HTML page (Bostock, Ogievetsky & Heer, 2011).

D3 focuses on selections within the canvas (section of webpage). One of the most important features of D3 is its ability to select all elements of a certain tag or class. Instead of changing all instances of a tag or class manually or using condition statements or loops, a single command can be used to select all of a specified object. Additional objects can be appended by entering objects and unwanted objects can be removed by exiting at any time. Entering and exiting are part of the enter, update, exit process when working with dynamic applications that are constantly changing. D3 utilizes these data-joins to allow the manipulation of a large portion of data and also provide an easy way to dynamically update graphs (Bostock, 2018). Additionally, there is a transition method which uses animations between updates to allow the user to follow changes in the data (Bostock, 2018). Scales are another powerful tool in D3. These act as objects and functions in order to keep data within axes, provide color changes, and do many other important tasks.

3.5.2 Data Availability Features

The following data availability features were added to the single_graph.html page of the OWLS using D3 as part of the JavaScript code. First, the date picker buttons, to choose the start data and the end dates, were added on the webpage (Figure 3-12), which allows a user to access LEWAS environmental data for any specific date range starting from February 2015 (the time from when LEWAS data has been stored in the database) to the current date. This is added to help users compare any past with a present environmental event. Second, the flexibility was added to the scatter plot graph to allow users for accessing one to maximum three plots on the page, which was earlier limited for accessing two to three plots at a time. This way, if a user wants to focus on just one plot or parameter, then there will be the option of only presenting one plot, allowing for less clutter on the graph. Users will also have the option to choose one to three parameters or plots for analysis and comparison. Third, a download button was added with which the users are able to download LEWAS data for the number of parameters/plots chosen and the date range selected on the start and end date button. In the other words, users are able to download the data that they are visualizing on the graph. The data are downloaded as separate csv files for each parameter having the parameter values and the corresponding time stamps. Due to the large amount of LEWAS data collected per day (~800 rows for one parameter for one day), the processing time needed to request and obtain huge amount of data from the LEWAS server becomes a constraint, which sometimes causes failure to access the data. To avoid such scenario, the data download feature allows users to access/download a maximum of one month (31days) of LEWAS data at a time. Any request beyond that time frame is denied and a message is shown to download data within one month period. Therefore, if users need to access data beyond one month, they need to download it multiple times choosing various date ranges. Fourth, the rawData.html page of the OWLS was recoded utilizing D3 to show values of a chosen parameter from a list of parameters in a tabular format (Figure 3-13). The data picker and data download buttons similar to the single_graph.html page, are added in this webpage so that users can pick an appropriate data and download the data, respectively. The data download feature improved the accessibility of the LEWAS data, which earlier had to be selected, and then copied and pasted in a csv files for analysis.



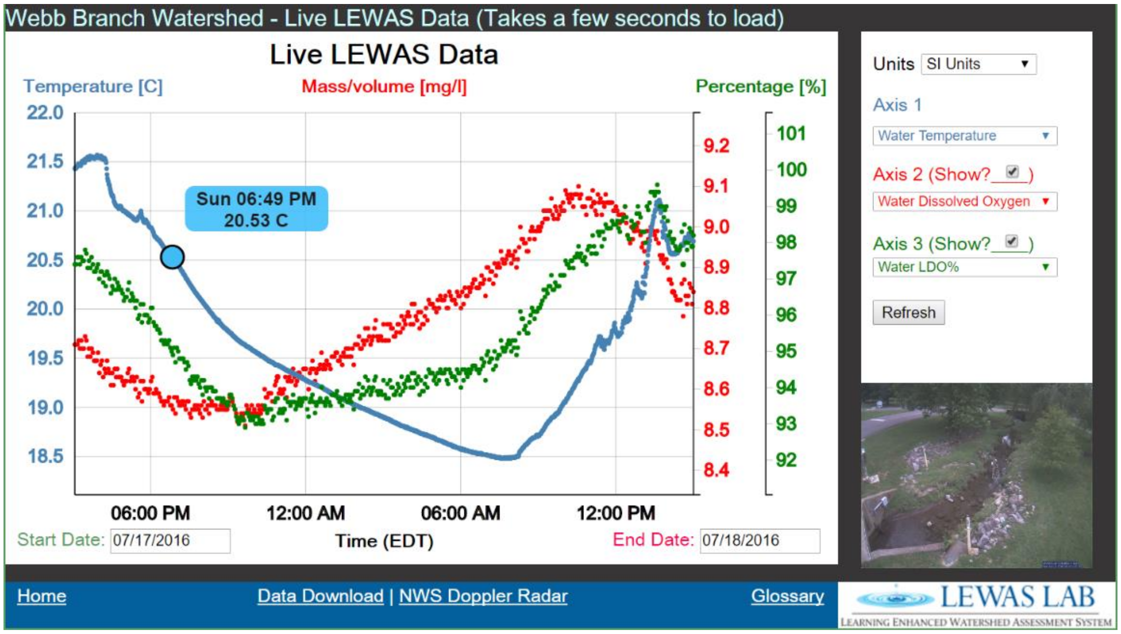
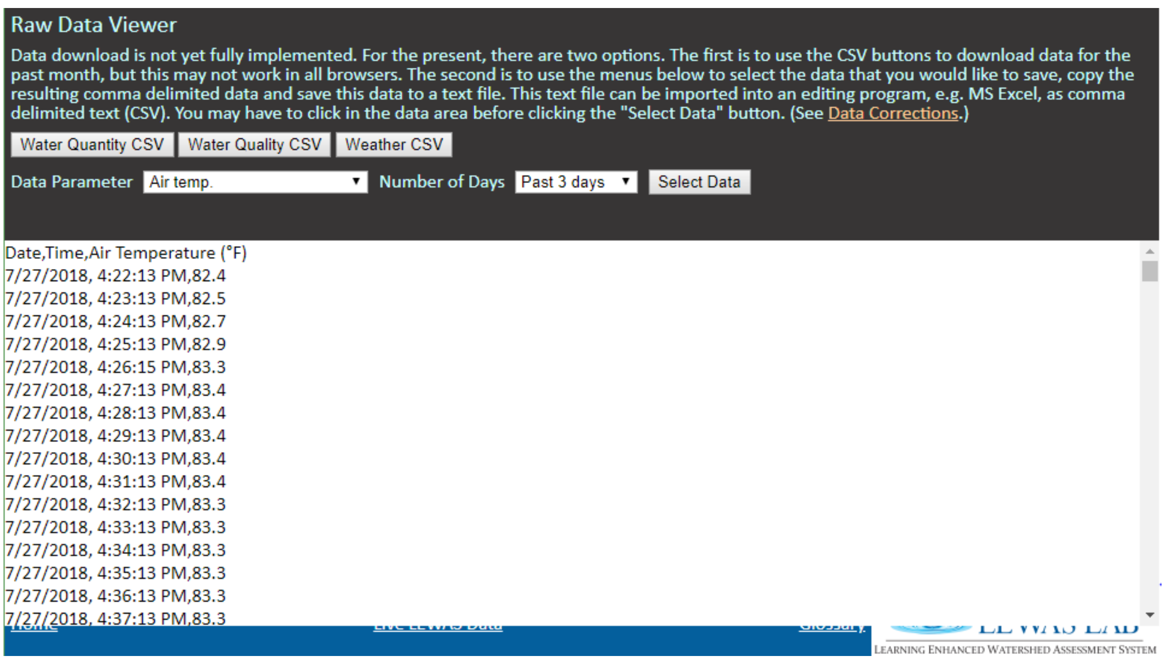


Figure 3-12. a) The single_graph.html page of the previous version of the OWLS, and b)The single_graph.html page of the OWLS with the new data availability and visualization features



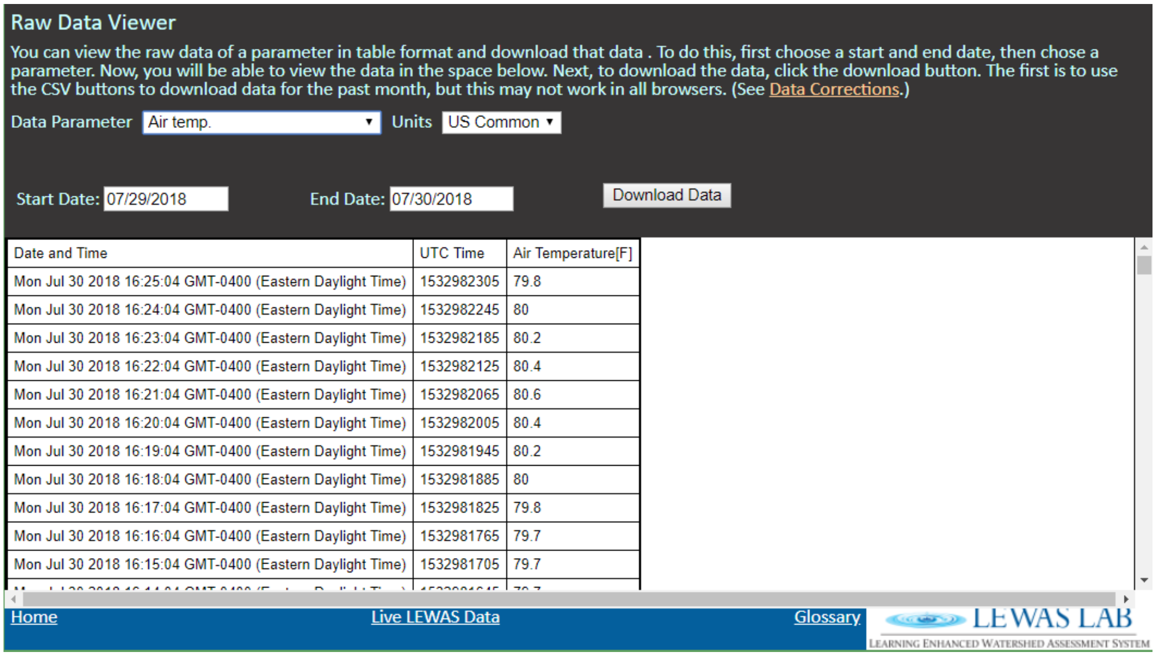


Figure 3-13. a) The rawData.html page of the previous version of the OWLS, and b) the rawData.html page of the new version of the OWLS with the new data availability features

3.5.3 Data Visualization Features

Data visualization features were added to the single_graph.html page of the OWLS using D3 to make it the page more interactive and effective in understanding the changes in the environmental parameters. First, a feature was added to increase the size of a data point if the user hovers over a data point on the plot. Along, with it the specific parameter value with corresponding timestamp also appears as a pop-out text within a tooltip to help reader in reading the values. Additionally, when the user clicks a point, features are added to make the data point even bigger with a border and different shade of the same color to emphasize the data point. The text within the tooltip becomes bolded to emphasize the values. These interactive features help with user-control by allowing the user to feel as though he or she has access to every specific point. The precise value shown makes the data easier to grasp. As a result, it becomes less abstract and more concrete. Second, the presentation of date and time on the x-axis of the plots were also improved. The default time interval or when users navigate to this page, it will show the data of the last 24 hours. If the time interval is within one day, then the x-axis tick labels show the time of day and the tooltip text will display the abbreviated day of the week and the specific time of day. This will help users understand the data by hour if one day worth of data is requested by them, which improves the readability of the data. If the time interval chosen by the user is greater than a day, but shorter than a week, then the x-axis tick labels will show the days of the week. The text on the tooltip will show the same information along with the time. It is assumed that the user is searching for the changes of the parameter by each day if a time interval shorter than one week is requested; hence the name of the day is shown to improve the comprehension of the data. If the time interval is greater than a week, the x-axis tick label will present the abbreviated month name and the date of the month. The same information will be shown in the tooltip text, but the time will be included as well. The weekday name is not provided in these cases since the weekday name is less beneficial than the specific dates for long time intervals. Third, the built in transitions option of D3, was used when new plot is drawn for a change in parameter. This feature makes the transition between different plots to be smoother, so the user can follow the changes rather than see a sudden, static re-plot (Bostock, 2018). The transitions were added to also provide better manipulation of the data. If the change is static, there does not always appear to be a difference in the data values, but when a dynamic transition is applied, the differences are easily followed.

In summary, the OWLS was advanced with the addition of the user-tracking system and data availability and visualization features. The user-tracking system was a full stack development following the Express framework. The system consists of server-side code written in Noje.js, client-side code written in HTML5, CSS, JavaScript and EJS, and a PostgreSQL database. It helps in identifying individual users, and detecting each user's interaction within the OWLS across devices. The data availability and visualization features, such as date picker and data point selector have been added by utilizing the D3 library of JavaScript, HTML5, and CSS. This development involved accessing a new version of LEWAS server, API and database, than the ones accessed by the earlier version of the OWLS. These new versions of the LEWAS server, API and database were being developed parallel to the advancement of the OWLS, which led the accomplishment of goal 1 to be more challenging than expected. All the program files related to this advancement of the OWLS are shown in Appendix C.

Chapter 4: Pilot Study and Results

This chapter includes the method and results from a pilot study conducted after developing the user-tracking system of the OWLS. The primary objective were to: 1) test the user-tracking system and collect user-tracking data, 2) develop and test an OWLS-based environmental monitoring task in a classroom setting, 3) collect students' perceptions towards learning using the OWLS with a post-survey, 4) collect students' perceived learning value of various components of the OWLS with a post-survey, 5) design a rubric based on students' responses to analyze students' learning with the OWLS-based task.

4.1 Method

An IRB (IRB #17-481) approved pilot study was carried out in Spring 2017 in two sections (Session1 and 2) of a course "Monitoring and Analysis of the Environment" (ENSC 4414) in the College of Agriculture and Life Science at Virginia Tech. An OWLS-based environmental monitoring task and an online post-survey were developed in consultation with the instructor. The specific learning objectives (LO) of the OWLS-based environmental monitoring task were to: LO1) determine the importance of continuous environmental monitoring data, and LO2) analyze, compare, contrast and interpret real-world environmental monitoring data. The LOs were consistent with the course learning objectives. The OWLS-based environmental monitoring task (Table 4-1) was designed as an in-class assignment that required students to explore various components of the OWLS and complete an electronically written report based on their findings. It was utilized for measuring individual student's learning utilizing the system. An online post-survey (Appendix A.A) was used to collect students' background information, their perceptions towards learning with the OWLS and their perceptions towards learning values of various components of the OWLS. The research design followed a pre-experimental design as shown in table 4-2, where students completed the environmental monitoring task using the OWLS and then completed the post-survey. As the students worked on the OWLS, their actions were tracked by the user tracking system and stored in the database. The items collected by it from each user are listed in table 4-3, which provides information for approximating individual students' variation in engagement while completing the OWLS-based task. To compare the individual students' learning with their engagement, the post-survey data, the OWLS-based task and the user-tracking data for each student were matched using their email ids (in this case it was their Virginia Tech' email ids). Thus, it was important that students use the same email id for signing into the OWLS, which could be matched to their email addresses used for submitting OWLS-based task on Canvas, and for completing the post-survey on qualtrics.

Table 4-1. 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 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 Online Watershed Learning System (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 watershed, 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 Watershed** Describe the Webb Branch watershed 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.

Table 4-2. Pilot study research design

Student Population	Self-Selection Sample (ENSC 4414)	Variation of Instruction (no variation)	Treatment	User Tracking data	Post-Survey
Students from a course meeting LO1 and LO2	Session 1 (n=10)	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.	OWLS-based environmental monitoring task	Data could not be collected for technical issues	Data Collected
	Session 2 (n=16)			Data Collected	Data Collected

Table 4-3. Items collected from each user by the user-tracking system

User's name, email and encrypted password (sign up information)
User's latitudes and longitudes
User's device information (e.g., desktop, tablet, mobile)
User's operating system
User's browser and version
User's webpage requests with UTC timestamp
User's actions within each webpage (e.g., button and video clicks, parameters chosen) with UTC timestamp
User's current webpage and status of whether he/she is "On OWLS" or "Off OWLS" at every minute

There were a total of 26 students: 10 from the Friday session 1 and 16 from the Monday session 2. Students were familiar with the OWLS as they had used it in a previous assignment. Therefore, without any demonstration of the system, students were given 2 hours of in-class time to complete the OWLS-based environmental monitoring task followed by the online post-survey. The post-survey was estimated to take about 10 minutes. However, for the post-survey, two of the questions did not work during session 1, for which students' email ids and gender information could not be collected. The post-survey was not setup properly and showed error during these last two questions. Also, the user tracking system did not work during session 1becasuse of a technical error related to the database. Both the post-survey and the user-tracking system were fixed and complete data were collected during session 2. Therefore, data on an individual level could be compared for only 16 students from session 2. Out of the 16 students, one student had a problem with his computer and could not participate in-class, but completed both the assignment and the post-survey as a home assignment. For this reason, the data of this student is excluded in many of the analyses. However, aggregate post- survey results are presented for all the students (n=26).

4.2 Results and Discussion

Students' background information. Most of the students (21/26) had taken or were currently taking a course Water Quality (ENSC/CSES 4314), which might have helped them to have better background knowledge for completing the task. According to students' self-assessment, they had different proficiency level in water quality concepts: 12 students were "advanced", 13 students were "intermediate" and 1 student was "basic". However, the instructor felt that they should all be capable to complete the assignment, which led us to implement the task in the course. Additionally, this course had already used the OWLS for a prior assignment in the course, which helped the students to have familiarity with the system. However, 11 out of 26 students mentioned in the post-survey that they did not use the OWLS earlier. Confirming with the instructor, it can be said that students might have wrongly interpreted the question or have forgotten about the earlier usage of the system while answering the post-survey. The effect of the differences among students in respect to their gender, background knowledge, proficiency level and familiarity of the system, was considered to be important to investigate during the final implementation with a bigger sample size. Due to small sample size (n=16) during the pilot study, these variables were not examined.

Students' self-perceived learning. For students' self-perceived learning, five questions were included in the post-survey that asked students about their agreement on a Likert scale of 1-6 (strongly disagree – strongly agree) on topics the OWLS helped them to learn. Among 26 students, 25 agreed or strongly agreed and 1 somewhat agreed that the OWLS helped them to learn about Webb-Branch watershed; all agreed or strong agreed that the OWLS helped them to learn the purpose/importance of continuous environmental monitoring; 19 agreed or strongly agree, and 7 somewhat agreed that the OWLS help them to relate theoretical knowledge to real-world water quality events happening at their local Webb Branch watershed; 21 agreed or strongly agree, and 5 somewhat agreed that OWLS helped them to know how to analyze environmental monitoring data; and 23 agreed or strongly agree, and 3 somewhat agreed that the OWLS helped them to identify real-world events. The average perceived value of learning was 5.27 out of 6 and the Std. Dev. was 0.56, indicating that students' thought that the OWLS was a helpful system for learning environmental monitoring concepts (Figure 4-1). These questions were planned to be included during final implementation of the study to assess students' perception of their learning with the OWLS.

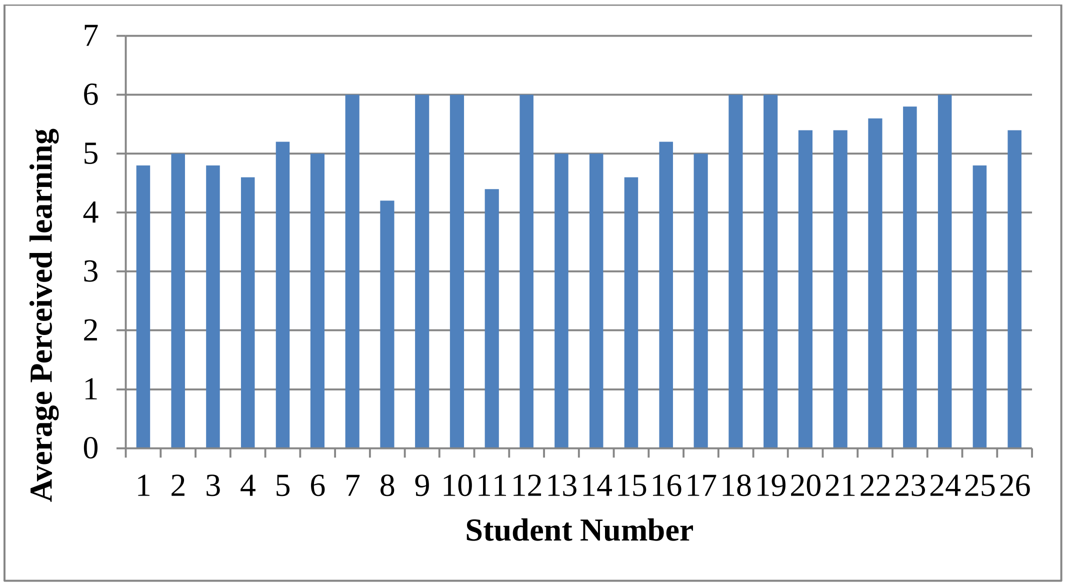


Figure 4-1: Perceived learning of all the 26 students

Students' perceived learning value of various components of the OWLS. For students' perceived learning value of various components of the OWLS, students rated each component of the OWLS with a scale of 1 to 4 (not valuable, somewhat valuable, valuable and extremely valuable). The average perceived learning value for each component as rated by 26 students were calculated and arranged in ascending order to observe the lowest to highest ranked features, as shown in Figure 4-2. It is to be noted that "Interactive Graphs" and "Live LEWAS data" are indicating the same page single_graph.html and was rated similarly by the students. Students also perceive highest learning value for the "Data download" page. This result indicates that students felt the data visualization and availability features were the most important components of the OWLS, which is consistent with previous OWLS-based research (Daniel, 2017). This result also ensures that increasing the data visualization and availability features, as is done in this study, is beneficial to increase the learning value of this cyberlearning system to the users. According to students, the components that ranked next were the “Background” and “Overhead view/map” followed by “Case studies”. These were the “must use” components of the OWLS for completing the environmentally monitoring task. Rest of the components of the OWLS, such as weather radar, storm view and glossary, were ranked lower by the students. This reason might be that students did not use these features of the OWLS for the task, and consequently perceived lower learning value of those components. These results indicate that students’ perceived learning value of various components of the OWLS might be related to the specific task requirements. In the final study, it was intended to repeat this part of the post-survey to explore the consistency of this result with a bigger sample size.

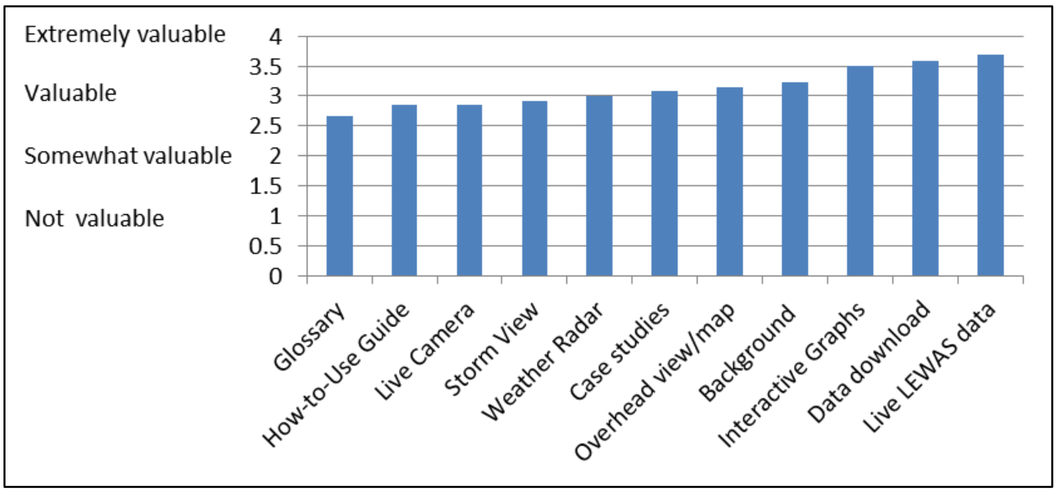


Figure 4-2: Students’ perceived learning value of various components of the OWLS

Conceptual Learning. To measure students’ conceptual learning, a rubric was iteratively developed to score the OWLS-based environmental task (Appendix A.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. Next, the rubric was verified with the instructor of the course that helped in addressing the construct validity of the rubric. The assignment responses of only the 16 students were graded as these scores could be compared with the other data sources. Figure 4-3 shows the grades of the 16 students out of a maximum score of 21. The grades for the 15 students, who completed the OWLS-based task in class, raged from 7 to 18, with a mean of 12.2 and std. dev. equals to 3.825; indicating that the scores are moderate and widely spread out. The16th student received a much higher score of 19.5 by completing the task as a homework assignment. This student might have received such high score, since he/she was able to explore OWLS with unlimited time and learn more. It will be interesting to investigate in future if time makes such difference in student learning with the OWLS.

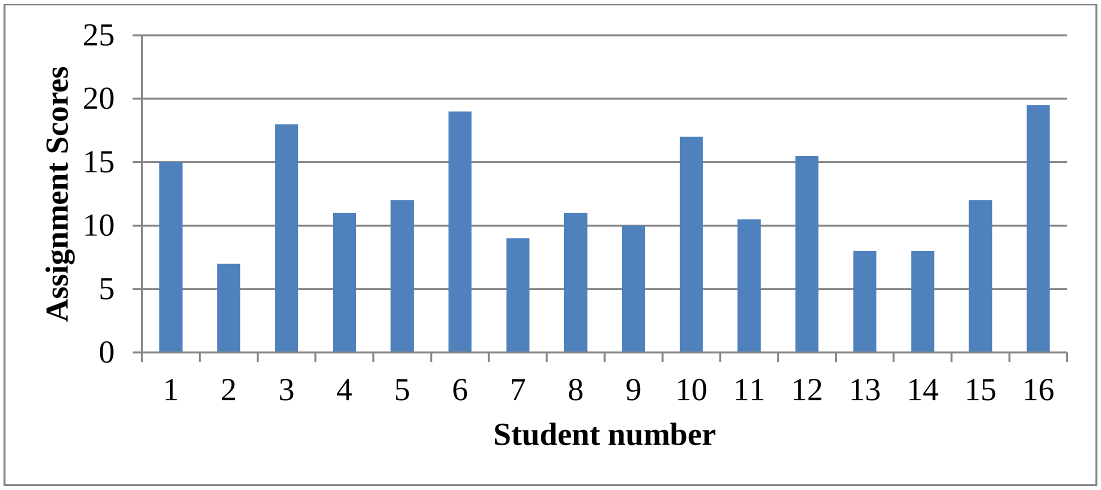


Figure 4-3. Conceptual learning scores for the 16 students from session 2.

Engagement. To measure individual student's engagement within the OWLS, the data collected by the user tracking system in the database for each student (n=16) was downloaded as separate excel files for exploration. The following values were calculated for further 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. Two of the students (student 7 and 8) did not log out, but the database recorded big time differences when their computers went offline with their browsers open near the end of the session. For these students, the time between their first visit to the OWLS and the time until the database recorded the big time difference was accounted for calculating the total time on task. This gave a more realistic estimate of total time on task. This time measurement can be assumed to be the total time a student had spent on their environmental monitoring task as it was observed by the instructor and the researcher that the students were either on the OWLS browser or on the word doc (hereafter referred to as task doc), where they were answering the task questions. Although, it should be noted that students were not restricted to not do any other activities during the in-class task. 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. It is the time when a student is is working on the task doc to report the findings or analyzing the environmental data downloaded from the OWLS or busy with other activities on his/her computer. “Off OWLS” time is used to account for the time students spent on the task document to complete the OWLS-based task being non-active on the OWLS. Making the assumption that the student was “Off OWLS” between consecutive “Off OWLS” 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 4-4. 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 level of engagement within the OWLS, and the total time on task can be considered as the measure of engagement with the environmental monitoring task. Table 4-4 shows the values for each of these measures for each student. To complete the full task in-class, students spent around 29 to 59 minutes with an average time 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. 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 significant and positive correlation ($\rho = 0.9$) at 0.01 level of significance, suggesting that either one it can be considered as a measure for engagement within the OWLS. The data of the 16th student indicates that if students were given the task as an homework, they might have taken much more time in completing it and spend more time on the OWLS.

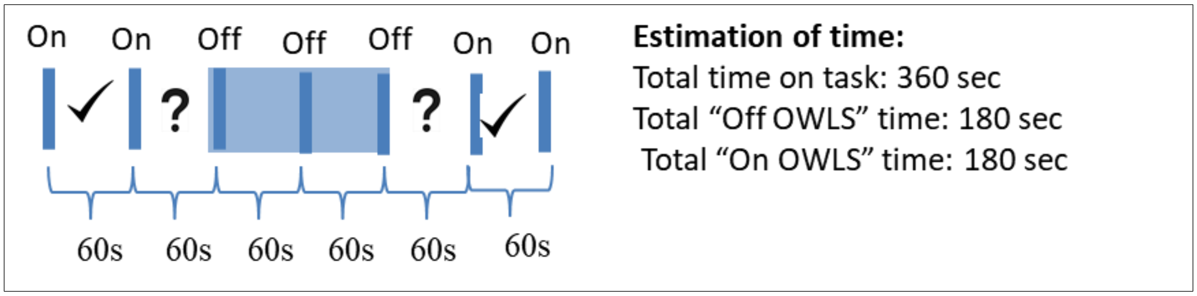


Figure 4-4. Calculation of the "On OWLS" and "Off OWLS" time with one "Off OWLS" time period

Table 4-4. Various measures for the level of engagement within the OWLS

Student #	Total time on task (min)	Total "Off OWLS" time (min)	Total "On OWLS" time (min)	Total number of clicks within the OWLS
1	58.28	46.43	11.85	28
2	30.85	20.03	10.82	26
3	30.78	18.15	12.63	25
4	29.48	17.08	12.4	29
5	59.22	49.46	9.76	21
6	52.48	45.02	7.46	23
7	45.58	28.01	17.57	35
8	49.71	29.03	20.68	42
9	41.68	25.05	16.63	33
10	58.38	38.28	20.1	41
11	36	24	12	22
12	36.35	30	6.35	10
13	34.05	19.01	15.04	30
14	26.16	9	17.16	44
15	47.26	36.05	11.21	24
Average Values for 15 students	**42.41733333**	**28.97333333**	**13.444**	**28.86666667**
16	163.01	114.03	48.98	68

Efficiency of the user tracking system. The pilot study results show that the developed user tracking system is able to track each student's engagement within the OWLS, which was a limitation of the earlier Google Analytics-based system (Brogam, Basu & Lohani, 2017). 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 Google Analytics-based system if it could be used for measuring individual engagement in this scenario. As shown in figure 4-5, the google analytics-based total "On OWLS" time (light blue bars) was compared with the total "On OWLS" (deep-blue bar) and "Off OWL" time (yellow) calculated by the new user-tracking system. It can be observed that for all the students, the earlier system over-estimated the total “On OWLS” time compared to the new system, providing evidence for the effectiveness of the new system. Google analytics overestimates the On OWLS time as it only accounts for the time when a user visits a webpage within the OWLS. Between each webpage visit a user might engage in other activities outside the OWLS interface, which is not detected by the google analytics system. Whereas, the new user-tracking system identifies the time when a user is using the OWLS actively and not using it along with the time of each webpage visits. This helps in calculating more accurate On OWLS time by deleting times when users were not actively using the OWLS. In addition, the new user-tracking system provides information to know when a user left OWLS (logs off), while the Google Analytics-based system is able to find the time when the last page was accessed by a user and not when they left that page. The user-tracking data also provides evidence that the new user-tracking system is compatible to several browser types and operating systems, without installation of any additional software. The operating system and the browser information that the user tracking system detected and stored for each student are shown in table 4-5.

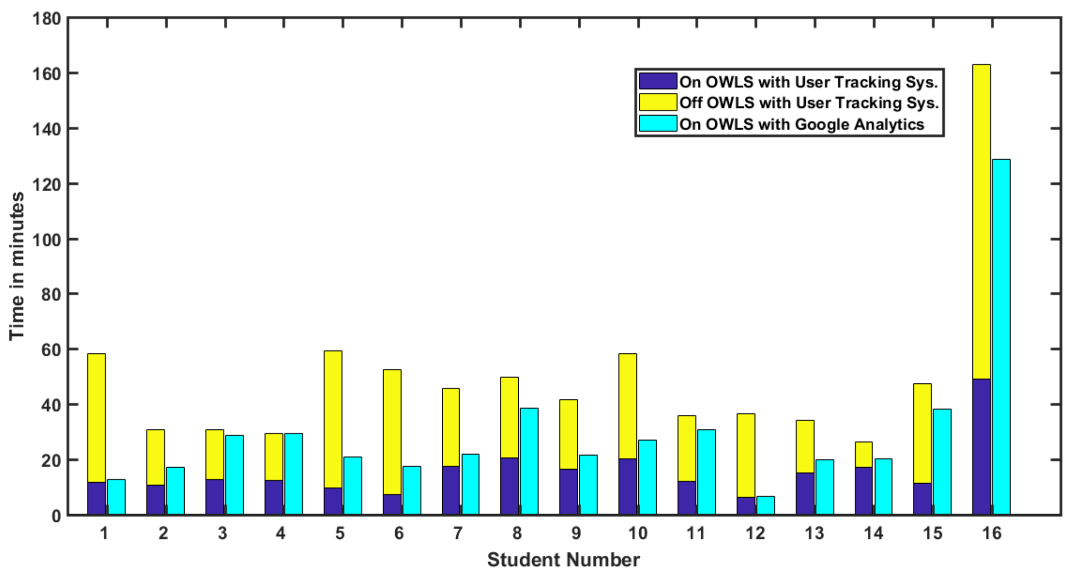


Figure 4-5. The user-tracking system compared to the earlier google analytics-based system.

Table 4-5. Students’ browser and operating systems.

Student #	Students’ Browsers	Students’ Operating Systems
1	Chrome 57.0.2987	Mac OS X 10.12.4

2	Chrome 57.0.2987	Mac OS X 10.9.5
3	Safari 10.0	Mac OS X 10.12
4	Chrome 57.0.2987	Windows 8.1
5	Safari 10.1	Mac OS X 10.10.5
6	Chrome 57.0.2987	Mac OS X 10.12.0
7	Chrome 51.0.2704	Windows
8	Chrome 57.0.2987	Windows 7
9	Chrome 57.0.2987	Windows
10	Safari 10.0.1	Mac OS X 10.10.5
11	Firefox 53.0	Mac OS X 10.11
12	Chrome 57.0.2987	Windows 7
13	Chrome 58.0.3029	Windows
14	Chrome 51.0.2704	Windows
15	Chrome 57.0.2987	Windows 7
16	Chrome 58.0.3029	Windows 7

Engagement patterns. Figure 4-6 shows the various paths taken by the individual students 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 web pages visited by the students within the OWLS during the total in-class time (3 to 4:15 pm). From this graph, various student engagement behaviors can be interpreted. 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, there seems to be a frequent activity trend in which students were accessing the system for this environmental monitoring 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 green). This type of pattern can be detected using sequential data mining algorithms (Kinnebrew, Loretz & Biswas, 2013), which is described in the next paragraph. Fourth, 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 2 browsers, then opened 4 browsers, which can be detected by the alternating colors in the graph. Fifth, it can be analyzed from the graph that 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 3.40pm. These types of information were helpful in understanding individual student's behavioral engagement pattern within the OWLS.

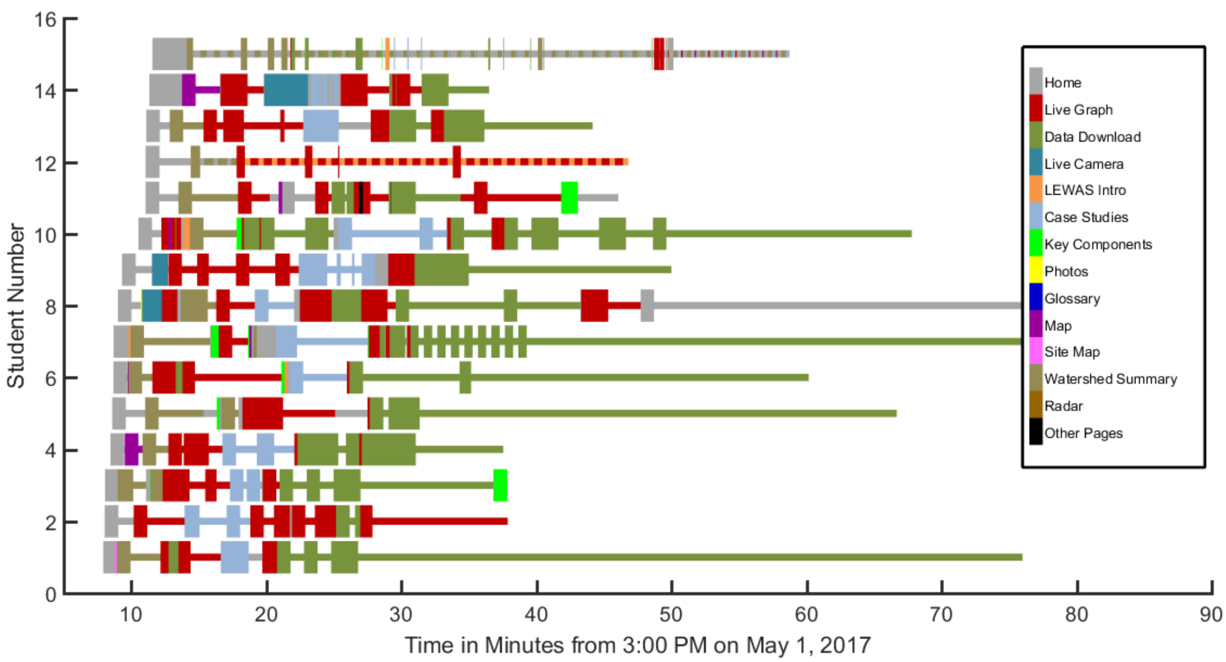


Figure 4-6. Various paths taken by each student to complete the environmental monitoring task.

Analysis of engagement patterns using a data mining technique. To further investigate the common patterns among these sequences, data mining techniques were explored. It was found that a sequence pattern mining (SPM) algorithm is able to detect the frequent patterns of actions within a group [37], [49], [50]. The advantage of using such data mining technique is to identify the frequent action patterns, which can provide us with more insights about the various students' learning strategies taken by them to complete the OWLS-based task.

In collaboration with a couple of colleagues from Vanderbilt University, a SPM algorithm was run on the temporal action sequences of the 15 students. To find useful patterns, the sequences were modified as follows. If there were a repetition of three or more similar actions, it was updated with a prefix “multi”. For example, if ‘index’ page was repeated thrice, the action would be replaced with index_multi. In the sequence pattern mining algorithm, a maximum gap size constraint of 3 is used. A gap size constraint of 3 means, a pattern might have maximum of three actions, which are not taken into account within consecutive actions in a pattern. Two measures in SPM algorithm to extract the students’ behavior are sequence (S-) support and instance (i-) support. S-support represents the proportion of students’ action sequences in which the pattern appears, and i-support is the average number of times a pattern appears in each individual student’s action sequences. In this analysis, we employed an s-support threshold of 50% to analyze patterns that were frequent. Some of the interesting patterns that suggest various strategies taken by the students in solving the OWLS-based task are shown in Table 4-6.

Table 4-6. Example patterns detected by the sequence pattern mining Algorithm

Patterns	**S-Support**	**I-Support**	**S-Frequency**	**I-Frequency**
1. single_graph_multi -> rawData_multi	0.8	1.13	15	17
2. index -> single_graph_multi -> rawData_multi	0.733	0.8	11	12
3. index -> watershed_summary	0.6	0.6	9	9
4. single_graph -> caseStudy	0.53	0.53	8	8
5. caseStudy -> single_graph_multi	0.53	0.53	8	8
6. single_graph_multi -> rawData_multi -> watershed_summary_multi	0.53	0.53	8	8
7. watershed_summary -> single_graph	0.53	0.6	8	9

The patterns are arranged in descending order of S-support number. It can be seen that pattern #1 was the most common pattern followed by all the students. This is because after students explored the data on the single_graph page, they had to download it from the raw_data page for data analysis. Pattern #2 is another common pattern found in the sequence of 11 students. The navigation system of the OWLS might have led to this pattern and students might have used this sequence of actions to complete the third part of the OWLS-based task, which asked students to analyze a specific conductivity event. Similarly, pattern #3 could have been used for answering the first part of the assignment, which asked students to describe the OWLS-targeted watershed. It is seen from patterns #4 and #5 that eight students were checking between the single graph and case study page. This was necessary for students to understand the benefits of continuous environmental monitoring, which was the second part of the assignment. Similarly, patterns #6 and #7 shows some common paths taken by at least 8 students to complete the OWLS-based task. The SPM algorithm helped in detecting the most frequent actions or strategies taken by the students to complete the OWLS-based task. These results also have implication for modifying the existing navigational system of the OWLS. For example, currently, students cannot go to the single graph page from the watershed summary page as seen in pattern #7. Students might have used different action in between these two actions to form the pattern #8. However, the SPM algorithm detected this pattern as a common strategy used by at least half of the students. Thus, navigation can be added from the watershed_summary to single graph page so that the system becomes more adaptable to the students for these kinds of tasks. Thus, applying the data mining technique helped in further exploring the user-tracking data and getting more insights into students' strategies. After the final implementation, a Differential sequential mining algorithm was utilized, to identify and differentiate the learning patterns between high and low scorers completing the similar OWLS-based task (Kinnebrew, Loretz & Biswas, 2013).

Resource Utilization. The user tracking data also provided information to understand how variedly each of the OWLS resources/components were utilized by the students for the specific environmental monitoring task. Figure 4-7 shows the number of clicks by the students on each of the accessed OWLS web pages. The total number of clicks includes the clicks for accessing each of the OWLS web pages as well as the total number of clicks within each webpage. 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. The pages with the watershed summary, components of the OWLS, LEWAS introduction and overhead view (or map) were moderately used. The other pages were very less used.

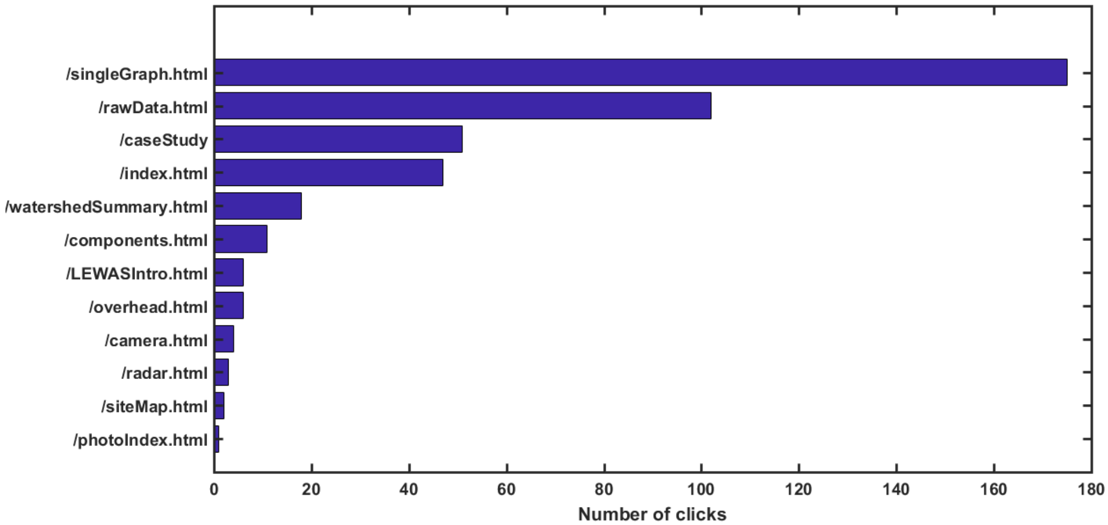


Figure 4-7. Total number of clicks for each of the OWLS web pages accessed by the students.

Data Comparisons. To further understand the relationship between students learning and variation in engagement within the OWLS, all the data found so far for students' perceived learning value of various components of the OWLS, their perceived learning with the OWLS, their conceptual learning scores and their level of engagement within the OWLS are being compared for the sample of 15 students. First, the relationship between the students' average perceived learning value of various components of the OWLS and the resource utilization i.e. total number of clicks on each of the OWLS web pages/components were investigated. This correlation was found out by matching the web page names in both these cases. The mismatch was handled in the following way: storm view page and glossary components of the OWLS were not accessed by the students, and thus assigned 0 for the number of clicks, while for background component of the OWLS, the clicks for both LEWAS intro and watershed summary were added. The Live LEWAS graph and the interactive graph components of the OWLS were referring to the same live graph page of the OWLS and thus assigned the same number of clicks for both. The result of the comparison shows that total number of clicks for each of the OWLS webpage shown in the figure 4-7 were significantly and positively correlated with the student perceived learning value of various components/web pages of the OWLS (figure 4-2) with a spearman coefficient of 0.89 at 0.01 level of significance, indicating a relation between them. In the final study, the survey will be updated so that the names of the various components of the OWLS match the names of the various web pages within OWLS for such comparison (figure 4-8).

Second, students' engagement was compared with their conceptual learning scores as from literature review it is known that engagement is generally positively related to a learning outcome, although it depends on the context of the cyberlearning system. For this, several spearman's correlations were carried out with the following measures of the engagement: total "On OWLS" time, total number of clicks within OWLS, total time on task and total "Off OWLS" time (table 4-4). While conceoual learning was measured by the assignment scores as mentioned earlier. The total "On OWLS" time had a low negative correlation (ρ= -0.31) with the assignment scores for 15 students. Similar results were found out when total number of clicks within OWLS for the same number of students was correlated with the assignment scores (ρ= -0.42). This result was counter-intuitive as it indicated that the less time students worked on OWLS, the more score they got. To explore further, total time on task was compared with the assignment score for 15 students, which showed a low positive correlation with Spearman coefficient (ρ) equal to 0.49. The trend in results indicates that if the sample size increases there might be a chance of positive and significant correlation between engagement with the task and conceptual learning. Although, it has to be noted that the pilot test did not restrict students' activity on their laptops during the in-class assignment, so if students were doing something else while working on the assignment, then the total time on task or total "Off OWLS" time might not precisely reflect the level of engagement. Therefore, the final study was designed in a way that, the learning environment is more controlled and the measurements are more appropriate.

Table 4-7. Comparison between level of engagement and conceptual learning for multiple measures of level of engagement and different sample sizes.

Different measures for Level of Engagement	**Conceptual 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

4.3 Summary of the Pilot Study Findings and Implications for the Final Implementation of the Study

Overall, the pilot study was useful in testing out the user tracking system, the post-survey, and the OWLS-based environmental monitoring task. This pilot implementation also led to the development of the rubric for accessing students' learning outcome. The post-survey data showed evidence that students perceived higher learning values of the data visualization and availability components compared to the other components. For this reason, advancement of the OWLS with more data visualization and availability features completed during phase 4 of the study was beneficial. The results also imply that students' perceived learning with the OWLS was higher compared to their conceptual learning scores. This shows that students' thought they learned more compared to their actual performance. Since students' initial knowledge was not measured, it was uncertain if there was any learning gain due to the OWLS-based task. For this reason, in the final implementation, along with the OWLS-based task, students were asked multiple choice questions based on OWLS content before and after the OWLS-based intervention.

The analysis of the user-tracking data shows that the user-tracking system is more effective than the earlier Google Analytics-based system, and provides a better time estimate of individual student's engagement time with the OWLS. The various engagement behaviors exhibited by the students while completing the environmental monitoring task were also detected using the user-tracking data. It was inferred from these data that students' usage of the system is potentially related to their familiarity of the system as well as the task requirements. The four measures of behavioral engagement, total time on task, total "On OWLS" time, total "Off OWLS" time and total number of clicks, portrayed different relationships with the conceptual learning. It will be interesting to observe if these relationships also emerge during the final implementation of the study. Additionally, students' usage of the OWLS components was positively and significantly related to their perceived learning value of different components of the OWLS. To further examine these trends and to examine the consistency of these results with a bigger population, the final implementation of the research was useful. Moreover, the final implementation of the study addressed the threats to the external validity of interaction of setting and treatment as it allowed the research to be conducted in a new setting (Creswell, 2013). Additionally, the final implementation with bigger sample size allowed examination of the effect of various variables (e.g., gender, and background knowledge) that might affect students' learning and engagement within 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 (O'Brien & Toms, 2008). To examine this relationship, the final study also included a user engagement scale (UES) for measuring the perceived engagement.

Chapter 5: Method for the Final Study

This chapter is organized as follows. Section 5.1 presents the research objectives along with the research questions. Section 5.2 includes the research design. The study participants and research settings are described in section 5.3. Section 5.4 includes the instruments and materials for the implementation. The experimental setup and data collection process are described in section 5.4. Finally, the data analysis steps are elaborated in section 5.5.

5.1 Research Objectives

The second goal of the study includes three research objectives:

1) evaluation of individual students' learning with the OWLS, and perceived learning value of various components of the OWLS
2) evaluation of individual students' engagement within the OWLS
3) exploration and determination of the relationship between learning and engagement

Table 5-1 summarizes the overarching research question, the research objectives, the research questions for each objective, the types of data, the data collection and analysis methods for the final study. The different types of data collected for each research objective and the purpose behind collecting such data are described below.

Table 5-1. Research questions, types of data, data collection and analysis methods of the final study.

Overarching Research Question: How do individual students learn and engage within a cyberlearning system (i.e., OWLS) to complete an environmental monitoring task?				
Research Objectives	**Research questions**	**Type of data**	**Data Collection Method**	**Data Analysis Method**
1. Evaluation of individual students' learning with the OWLS, and perceived learning value of various components of the OWLS	How do students perceive their learning with the OWLS?	Perceived learning	Post-survey data	Descriptive statistics, and inferential statistics
	What are students' learning outcomes with the OWLS?	Conceptual learning	Pre and Post-content-based survey data, OWLS-based task scores	
	What are the students' perceived learning values of various components of the OWLS?	Perceived learning value of various components of the OWLS	Post-survey data	
2. Evaluation of individual student's engagement within the OWLS	How much students are engaged with the OWLS?	Behavioral engagement	User tracking data	Descriptive statistics and inferential statistics
	How much OWLS resources are being utilized by the students?	Resource utilization		Descriptive statistics, Data visualizations
	What are the various paths taken by the individual students within the OWLS for a specific environmental monitoring task?	Engagement pattern		Data visualizations, Data mining algorithm
	What is students' perceived engagement with the OWLS?	Perceived engagement	User Engagement Scale data from Post-survey	Descriptive statistics and inferential statistics
3. Exploration and determination of the relationship between learning and engagement	How does students' engagement within the OWLS relate to their learning for a particular environmental monitoring task?	All learning and engagement data	All above-mentioned data	Descriptive statistics - Correlational Analysis
	How does students' resource utilization within the OWLS relate to their perceived learning value of various components of the OWLS?	Resource utilization and Perceived learning value of various components of the OWLS		

The first research objective focuses on measuring students' learning with the OWLS. Similar to the pilot implementation, learning was measured in two ways: conceptual learning and perceived learning. To measure conceptual learning, an OWLS-based environmental monitoring task, similar to the one used in pilot study, was developed. To grade the task, the rubric used in the pilot study was adapted (details provided in section 5.5). Students' grades on the environmental monitoring task were used to understand students' learning outcome utilizing the OWLS. It was difficult to understand students' gain in knowledge with the grades on the OWLS-based task. Thus, in this final implementation, the conceptual learning was also assessed with 9 content-based multiple choice questions, which were added in the pre and post-surveys to find out the learning gain due to the OWLS-based intervention. Additionally, perceived learning questions used in the pilot study were added to the post-survey for collecting students' perception of their learning with the OWLS after completing the OWLS-based environmental monitoring task. All these learning data was used for evaluating the individual student's learning with the OWLS in multiple ways that provided the opportunity to compare different datasets. Moreover, each student's perception on the learning value of the different components of the OWLS was also collected using the post-survey. This information was essential in understanding students' opinion about the system as a learning tool, and could be compared to their learning and engagement to gain insights.

The second research objective was focused on evaluating students' engagement within the OWLS. Engagement was measured at the individual level in two ways: behavioral engagement and perceived engagement. Similar to the pilot study, the behavioral engagement data was collected using the user tracking system, while students were completing the OWLS-based environmental monitoring task. As shown in the pilot study, user tracking data can provide the approximation for the students' engagement in four different forms: total time on task, total "On OWLS" time, total "Off OWLS" time and total number of clicks. Additionally, the user tracking data is also effective in determining the patterns of students' engagement within the OWLS across time, and the resource utilization of the

OWLS. Perceived engagement was measured using the user engagement scale (UES), which was not employed in the pilot study. This self-reported data complement the behavioral data by providing the scope to characterize the psychological state of students' engagement (O'Brien & Cairns, 2016). This approach is utilized for investigating the relationship between students' perceived and behavioral engagement, which helps in exploring students' engagement within the OWLS in a complete way.

For the third research objective, all the variables measured for the learning and engagement will be compared to examine the relationships between them. The relationship between resource utilization and students' perceived learning value of various components of the OWLS will also be investigated. These comparisons will help to understand the dynamics between individual student's learning and engagement in the context of the OWLS. Some of these initial trends were found out in the pilot study. For this final implementation, a similar study design is chosen with a bigger sample size, so that the trends can be confirmed. In the subsequent sections, the research design, the participants, the experimental setup, data collection and data analysis methods are elaborated.

5.2 Research Design

To answer the research questions presented in Table 5-1, a pre-experimental quantitative research design was chosen. In this case, the aim was to investigate how one group of students from an undergraduate engineering course learn and engage within the OWLS when they are completing an OWLS-based environmental monitoring task within a classroom environment. According to Creswell (2013), a pre-experimental design is appropriate when the study intends to test the impact of an intervention with a single group. Table 5-2 outlines the details of the pre-experimental setup. For this research, a convenience sampling strategy was used to choose the sample for the study. A junior level engineering course was chosen for the study and an OWLS-based task was designed to evaluate students' learning related to water quality. It was assumed that all students have an equal amount of interest in learning using a cyberlearning system. The students were asked to complete a pre-survey before the OWLS was introduced to them. Two consecutive class sessions were chosen for the implementation. The first session was a training session with the OWLS, and the second session was allotted for students to complete an OWLS-based task. The OWLS-based task had two versions, set A and B (Appendix B.E), with same questions but in different sequence. Students were randomly chosen for each set. A post-survey was given immediately after the intervention. To make the OWLS-based intervention as a part of the course, students' reports were graded any other homework assignment in the class. The aim was to let students complete the task to gain knowledge, and not to engage in the task for accomplishing a study activity. This approach was effective in collecting the data in natural setting and not by incentivizing students, which often leads to biased results (Baltierra et al., 2016). However, to complete all the four activities: the pre-survey, the training session and the OWLS-based assignment during the class time, and the post-survey, students were given a minimal credit of 3-points. This was intentionally planned to increase the participation in the study. If students decided not to participate in the study, they had other means to earn these credits in the course. This study design was approved by the Institution Review Board (IRB).

Table 5-2. Pre-Experimental Research design for the final study.

Convenience Sample	**Pre-Survey**	**Session 1** (45 min on Tuesday of Week 5)	**User Tracking Data Collection**	**Session 2** (100 min on Thursday of Week 5)	**User Tracking Data Collection**	**Post-Survey**
Students from a section of CEE 3104		Demo of the OWLS and data analysis by downloading data from the OWLS		OWLS-based environmental monitoring task		

5.3 Study Participants and Setting

The IRB-approved (IRB #17-481) study was conducted during Fall of 2017. For this study a junior level course "Introduction to Environmental Engineering" (CEE3104) in civil and environmental engineering (CEE) department at Virginia Tech was selected as the setting. A section of this course having 59 students served as the study site. The instructor of the course was part of the study as a domain expert. A part of the course objective was dedicated to "water quality concepts", which seemed to be fit for the OWLS-based implementation. Accordingly, with consultation with the instructor of the course, the research implementation plan was made. The instructor made the researcher the teaching assistant for the OWLS-based implementation and gave access to the canvas site of the course. The students were mostly from CEE. An email was sent to all the students for inviting them to participate in the study. The consent to participate in the study was included in the survey, which included consent for allowing researchers to analyze their OWLS-based task responses and their actions recorded by the user tracking system of the OWLS during the week of implementation (week 5) and also to collect their course grades. Students consent to participate in the study was implied by the submission of the surveys. The decision to participate or not to participate in the survey did not affect students' grades on the OWLS-based task, which was named as "water quality project" for the class. Out of the 59 students, 52 students participated in the study by completing all the study activities (the pre-survey, the training session, the OWLS-based assignment during the class time, and the post-survey) and earning the extra-credit of 3-points. The students, who did not participate in the study, completed the OWLS-based task and received their grades on the task. These students had the option to earn their extra-credits by participating in other extra-credit assignments in the course.

5.4 Instruments and Materials

The following instruments and materials were prepared for the final study.

Pre-survey. A pre-survey was developed in qualtrics as an online survey with 15 items. It was confidential but not anonymous. It contained consent information and closed-ended questions on students' background and content questions for measuring students learning gain. Background question asked information about students': VT email id, gender, ethnicity, proficiency level in water quality, and the number of water resource/quality courses taken by them except the present course and the name of those courses. These were potentially the control variables, which could impact the learning outcome (dependent variable) as understood from the pilot study. The pre-survey also included 9 multiple-choice content questions targeted to measure students' initial knowledge in environmental monitoring concepts. These questions were aligned with the content for the OWLS-based task. The questions were developed in consultation with the domain experts to address the construct validity of the questions. Construct validity assesses the accuracy with which variables are operationalized to measure the outcomes of interest (Krathwohl , 2009; Cook, Campbell & Shadish, 2002). Additionally, particular attention was given in developing this survey so that students do not come to know about the OWLS before the actual implementation, which could affect the results. The pre-survey is shown in Appendix B.A. The survey would take maximum 10 minutes to complete. Below are two sample content questions.

- Solubility of oxygen is higher at 0 deg C compared to at 15 deg C:

  True (1)

  False (2)

- Data errors from the continuous water quality monitoring station can always be attributed to environmental (natural) factors:

  True (1)

  False (2)

Materials for Training Session. For introducing students to the OWLS during the training session, the following materials were prepared: a short presentation (Appendix B.B), an instruction sheet (Appendix B.C), and a sign-in/attendance sheet (Appendix D). A 10 min short presentation was prepared to provide students a background of the LEWAS and the OWLS and the purpose of the study. The instruction sheet was prepared to guide students using the OWLS, as it was new software for them. The instruction sheet had directions for students to: sign-in to the OWLS with their VT email address, save their password, explore the OWLS, use one browser to access the OWLS, and complete few OWLS-based practice problems and logout. The practice-problems were also added in the instruction sheet. The problems were designed for students to get habituated using the OWLS. It was intended for to help them prepare to complete the OWLS-based task independently. This was done to avoid any bias that might affect the study due to students not being able to handle the software. The sign-in sheet asked students to fill the following: First name, Middle name, Last name, Email Id used for OWLS login. This was collected as an extra measurement for verifying students' attendance and their email id.

OWLS-based task. An OWLS-based task was developed for the implementation and was called a "water quality project". It was adapted from the OWLS-based task used during the pilot study but tweaked to accommodate the objective of the particular course. The modification was done in consultation with the domain experts to address the construct validity as well as to fit the particular student sample. The feasibility, scope and time required to complete the task was tested during pilot study, which helped in its implementation (Singleton & Straits, 1999). The OWLS-based task is shown in appendix B.E that consists of some instructions and the task. The instructions were given to ensure that students are only completing the OWLS-based environmental monitoring task during the session and the user-tracking data only reflect students' behavior related to this task and not any other task/s. This process was followed to overcome the limitation of the data collected during the pilot study. Similar to the instruction sheet, the below instructions were given to the students for the proper implementation of the OWLS-based task:

1. Login to the OWLS with your VT email address and password
2. Use only one browser to access the OWLS
3. Do not use any other browser for any other task
4. Do not engage in any other task while completing this project on your own
5. Logout (link on the home page) from the OWLS after completion of the project
6. Submit the project report/response document to canvas under homework
7. Complete the post-survey (voluntary) after completing the project [link provided in the canvas announcement].

There were two versions of the task, set A and B, with same set questions but in a different sequence. This provided the opportunity to examine the impact of different instructional design with a cyberlearning tool, like the OWLS. The task had three main parts that asked students to do the following: 1) describe the Webb Branch Watershed, 2) identify the benefits of continuous environmental monitoring as is being done at the LEWAS site, 3) analyze and compare Dissolved Oxygen (DO) and Water

Temperature (WT) data from the LEWAS field site. Each part 1, 2 and 3 were designed to correspond from lower to higher levels of blooms taxonomy. The OWLS-based task was designed to evaluate students' learning up to the fourth level of Bloom's taxonomy (analyze) using the OWLS, which was not possible with the content questions. Under each of the three parts, there were more in-depth questions. The above sequence of part 1, 2 and 3 was followed for set B, while set A had the sequence as part 3, 1 and 2. The OWLS-based task was estimated to be completed within the 75 min of class time, since students completed a similar task within 60 min during the pilot study.

Post-survey. The post-survey was also designed as a qualtrics online survey with 57 items. It was estimated to take about 20 min to complete the survey. The post-survey had questions related to students' proficiency level in water quality concepts, students' perceived learning with the OWLS, their perceived learning value towards the various components of the OWLS, the content questions asked in the pre-survey and the User Engagement Scale (UES) items to collect information about students' perceived engagement within the OWLS. Among these, the first three types of question were tested during the pilot study. For the questions related to the perceived learning value for the various components of the OWLS, the component names were updated to the names of the different web pages on the OWLS. This was done so that students can clearly recognize each webpage. A discussion of the origin, validity and reliability of the 31 UES items are highlighted in section 2.5.2.4. It also included question that asked students about the following: if they had accessed OWLS in any of their previous courses other than the current course and the name of the corresponding course, if they have accessed OWLS before week 5 in the course, and the way they have accessed the OWLS for completing the OWLS-based task. These questions were targeted to understand if students had previous familiarity with the OWLS. Few open-ended questions were also asked to understand students' opinion on their learning after completing the OWLS-based task, and their overall experiences and challenges faced while completing the OWLS-based task. The complete post-survey is shown in appendix B.G. Below are few example questions for each category of items to demonstrate the type of questions that were given to the students.

- **Students’ perceived learning with the OWLS**:

  The OWLS helped me know how to analyze environmental monitoring data:
  - Strongly agree
  - Agree
  - Somewhat agree
  - Somewhat disagree
  - Disagree
  - Strongly disagree

- **Students’ perceived learning value towards the various components of the OWLS:**

	Not valuable	Somewhat valuable	Valuable	Extremely valuable
Overhead view/map	❍	❍	❍	❍
Case studies	❍	❍	❍	❍
LEWAS Intro	❍	❍	❍	❍

- **Items from User Engagement Scale** (5-point likert scale, strong agree to strongly disagree):

  Focused Attention:
  I "lost myself" in this OWLS-based experience
  Felt Involvement:
  I was really drawn into my OWLS-based project
  Novelty
  I continued to explore OWLS website out of curiosity
  Endurability
  My OWLS-based experience was rewarding
  Aesthetics
  This OWLS website was aesthetically appealing
  Perceived Usability
  I felt in control of my OWLS-based experience

5.5 Experimental Setup and Data Collection

An email announcement was sent during the end of the first week of the class for inviting students to participate in the study and to complete the pre-survey. The email contained the consent information and the link to the pre-survey. The pre-survey was open for two-weeks for students to complete the survey. During both the weeks, a reminder about the pre-survey was included in the weekly update emails of the course sent by the TA to the students.

During week 5 of the class, the OWLS was implemented in two consecutive sessions, 1 and 2 of the course. During session 1, the author took the last 45 min of the class to introduce students to the

OWLS and its various components and features. The training session was intended to help the researcher clarify questions related to the OWLS accessibility/technical issues so that students can independently complete the OWLS-based environmental monitoring task during session 2. This was important for avoiding instructor/researcher bias on the students' response to the OWLS-based task and students' exploration of the OWLS during the OWLS-based task. All the students were able to sign in to the OWLS and explore most of its pages. However, due to technical reason, students were facing issues while accessing data on the single_graph.html page as they were all trying to load the page at the same time. This issue along with the time constraint led the research to ask students to log out of the OWLS. The researcher completed the training session by showing students the intended use of each of the OWLS components while going through the practice problems and discussing the solutions with the students. Students were then asked to explore OWLS on their own before session 2 so that they can complete the OWLS-based task independently during session 2. Students were also allowed to visit office hours if they had queries related to completing the practice problems with the OWLS. In the meantime, the technical issue was fixed by implementing some updates on the LEWAS database containing the environmental data.

During session 2, students were asked to complete an OWLS-based environmental monitoring task within the class time. The session time was considered as 100 mins as some of the students had logged into the OWLS in anticipation of the task as soon as they entered the class 10 min before the start time, 75 min of in-class time and 15 min of extra time. Students were given a physical copy of the task and the sign in sheet. Students primarily worked themselves on the task. If they had questions, they asked the TA or the researcher, who were both present in the class. Answers were given to students if it was related to interpreting the questions on the OWLS-based task. Students were asked to use VT email id for their pre and post-surveys, the sign-in process of OWLS and the canvas submission of their report on the OWLS-based task to ensure that the data of the individual students across various sources can be compared. The browser usage was restricted to one browser for accessing the OWLS for ease in data analysis (Ahmadi & Jazayeri, 2014).

The email announcement with the post-survey link was sent out during the middle of the class so that students can only attempt it after completing their OWLS-based task. Students were invited to participate in the online post-survey immediately after completing their task. Since students might not be able to complete their survey during the class time; they were encouraged to take the survey within a week. Literature suggests administering self-reporting surveys just after the intervention so that students can reflect on most of their experiences (O'Brien & Cairns, 2016).

Several factors have been taken into consideration for this OWLS-based intervention. The history and maturation threats to internal validity might have happened in this setting as students learned about various environmental concepts in the course between the pre and post-survey and there might a change in knowledge level. However, it will be mostly addressed as the full group of students will experience the same external events and their maturation in knowledge will be similar (Creswell, 2013). Internal threat to mortality, which indicates that students might drop out of the study, was anticipated to happen in this scenario. It was decided that students, who drop out of the course, their VT email id will be detected with the help of the instructor, and their data will not be included for analysis. The threat to diffusion of treatment has been avoided by not having a control and experimental group from the same group of students. Having all the students experience the treatment in the similar way also addressed the issues of compensatory demoralization and compensatory rivalry. Again, the threat to instrumentation is addressed by having same content questions in the pre and post-survey. Although, the test-retest threat to internal validity might still exist, it was addressed by having sufficient time period between the pre and post-survey. Finally, in-class time was selected for the implementation to control the learning environment as much as possible, which will help in avoiding confounding variables that might affect the study outcome. For example, if students were completing the OWLS-based task as an homework, the off OWLS time might include times when students were doing things other rather than the OWLS-based task and thus, the Off OWLS times would not reflect the correct values.

5.6 Data Analysis

The analysis phase includes: 1) data preprocessing, 2) data exploration and 3) data inference. Statistical software JMP, programming tool MATLAB, and Microsoft Excel were used for data analysis. The data analysis techniques used for each research question are shown in table 3-7.

Data preprocessing. For this step, first, the *rubric* for the OWLS-based task was prepared (Appendix B.F). The rubric for the final implementation was adapted from the pilot implementation. It was updated for the specific requirements of the task. It was then used by the researcher and the TA of the class to grade few randomly picked but same task responses, respectively. Accordingly, changes on the rubric were discussed and finalized. The final rubric was verified with the instructor of the course to ensure the construct validity of the rubric (Creswell, 2013). It was then used by the researcher to score all the OWLS-based task responses out of 20. To establish the inter-rater reliability of the scores on the OWLS-based task, it was graded by both the TA of the course and the researcher and compared (Moskal & Leydens, 2002). The finding is presented in the result section.

Second, PostgreSQL queries were utilized to extract user-tracking data from the database for individual students and for creating csv files for each of them. For example, Figure 5-1 shows the typical steps including the PostgreSQL queries utilized to download such data. In total 12,919 records of data of all the students' interaction within OWLS were saved in 52 Excel files for further analysis. Third, these Excel sheets were read in MATLAB for writing various algorithms to calculate certain parameter values and draw data visualizations. For example, a MATLAB code was written to calculate the total On OWLS time and total Off OWLS time for each student, a part of which is shown in Figure 5-2. One common part of every code was to extract the user-tracking data of the session 2 in-class time period, which was considered as 100 mins by including: 10min before the class started as few of the students had already logged in to the OWLS in anticipation of the OWLS-based task, 75 min of in-class time and 15 min after the class ended as few of the students took little more time in completing the task. These algorithms can be later utilized to build dashboard features with OWLS. Fourth, the pre and post-survey data were joined for individual students in JMP and the values calculated with MATLAB and rubric for each student was added to the file. Next, the data were prepared and cleaned for quantitative analysis using the JMP software. For example, the Likert scale responses are converted into numbers so that quantitative analysis can be carried out.

```
Last login: Thu Jun 14 13:50:54 2018 from 128.173.40.161
lewas@lewas-api:~$ psql owlsusers
psql (9.5.12)
Type "help" for help.

owlsusers=> Select * from users where email='debarati@vt.edu';
owlsusers=>
owlsusers=> \COPY (Select * from requests where uuid='ee[redacted]8ece
b' order by req_time asc) TO '/tmp/99.csv' DELIMITER ',' CSV HEADER;
COPY 28
owlsusers=> \q
lewas@lewas-api:~$ exit
logout
Connection to 128.173.221.23 closed.
~  > scp -r lewas-api:/tmp/99.csv Workspace/;
99.csv                                        100% 5070     5.0KB/s   00:00
~  >
```

Figure 5-1. An example code snippet for showing the PostgreSQL queries needed for downloading user-tracking data of each student in csv format from the “owlsusers” database in the LEWAS server (lewas@lewas-api).

```
            %calculating the timeOnTask
            if time_diff_R(count)<200
            timeOnTask(student_id) =timeOnTask(student_id) +  time_diff_R(count);
            end
            %calculating the offowlsTime
            if time_diff_R(count)>=59 && time_diff_R(count)<=200
                if  user_params_R(count)=='inactive'
                     offOwlsTime(student_id) = offOwlsTime(student_id) + time_diff_R(count);
                end
            end

            count=count+1;

        end
    end
end
      clicks(student_id)=count-clicks(student_id)-1-(CountSingleGraph*3); %calculating the number of clicks
      offOwlsTime(student_id) = offOwlsTime(student_id)/60; %calculating the offowlsTime in minutes
      timeOnTask(student_id) =  timeOnTask(student_id)/60;  %calculating the timeOnTask in minutes
      onOwlsTime(student_id) =  timeOnTask(student_id) - offOwlsTime(student_id);  %calculating the onOwlsTime in minutes
```

Figure 5-2. An example of a part of a MATLAB code written to calculate the total time on task and total Off OWLS time for each student.

Data exploration. For this step, first, descriptive statistics, such a mean, median and standard deviations were used to explore each of the variables in the study and to summarize it in the context of the sample (Ott & Longnecker, 2015). For example, to understand the average time students had spent on the OWLS and the variation of this time between the students for completing the OWLS-based task, the mean On OWLS time and its standard deviation were calculated. Second, to understand and gain more insights from combining different kinds of data, various graphical visualizations were created using MATLAB. For example, a graph was built to visualize the number of times each of the different types of OWLS components was utilized by each of the high and low performing students for completing the OWLS-based task. Third, to find the relationship between two variables, correlational analysis was carried out. Correlation analysis is an approach to find out if a change in one variable is like to be related to the change in another variable. To find the strength and direction of the linear relationship between two variables, correlational coefficients are calculated. The value of the coefficient close to +1 or -1 denotes very strong positive or negative linear relationship, respectively, while a value close to 0 shows a weak linear relationship (Ott & Longnecker, 2015). For normally distributed variables, Pearson product-moment correlation was used; otherwise Spearman rank-order correlation was utilized. For example, Pearson product-moment correlational analysis between individual students' "On OWLS" time and the total number of clicks on the OWLS was carried out to find the relationship between these two variables. Finally, Cronbach's alpha test was carried out for establishing the internal reliability of the various items within a scale of the surveys (Allen, Reed-Rhoads, Terry, Murphy & Stone, 2008). For example, for the UES data, Cronbach's alpha value was found out for each of the attributes of perceived engagement to find the internal reliability of the sub-scales.

Data inference. For the third step, inferential statistical techniques were used to deduce various conclusions about the data set. In the cases where the central limit theorem was satisfied, paired t-tests and independent t-tests were utilized to check if the means of a variable between two different groups of students or one group of students at different times, respectively, are reliably different (Ott & Longnecker, 2015). For example, paired t-tests were carried out between the pre and post-survey responses to each of the content questions to investigate the learning gain with the OWLS. Independent t-tests was planned to be used to identify if there was a difference in the mean number of clicks that students' utilized to complete the OWLS-based task between the high and low scorers. But in most cases where independent t-tests were planned, the sample size of each group did not satisfy the central limit theorem. Thus, in those cases where the central limit theorem did not satisfy, non-parametric tests were selected (Ott & Longnecker, 2015). For paired samples, non-normal distribution of data, Wilcoxon Signed Rank Test was utilized. For independent samples, non-normal distribution of data, Wilcoxon Rank Sum non-parametric test was employed. For Wilcoxon Rank Sum non-parametric test, the sample size of both the groups had to be greater than 10, which was satisfied in this study. The effect size was also calculated to find out the standardized difference between the two means that can demonstrate the significance of any difference as statistical significance can be affected by sample sizes (Cohen, 1988). Cohen's d or Hedges' g can be used to calculate the effect size (Ellis, 2009). Cohen's d formula is used when the samples of the two groups are of same size (Cohen, 1988). When the sample sizes of the two groups were different, for which the standard deviation of each group needs to be weighted by the sample size, the Hedges' g formula is chosen (Hedges, 1981). An example calculation of effect size using Hedges' g formula is shown in Appendix B.I. Ranges of effect size as applied to social science research are- near zero: $d \leq 0.10$; small: $0.11 < d \leq 0.35$; moderate: $0.36 < d \leq 0.65$; large: $0.66 < d \leq 1.0$; and very large: $d > 1.0$ (Sawilowsky, 2009).

Further, a data mining technique called *Differential Sequence Mining (DSM)* was used to analyze the precise differences in learning behavior of the students while completing the OWLS-based task as detected by the data visualization on the temporal navigation pattern of the students. Compared to the Sequence Pattern Mining algorithm used during the pilot study that detected the frequent patterns (or sequence) of actions within a group, this DSM techniques goes one step further to identify the common learning patterns and then differentiate the patterns between two groups completing a similar task (Kinnebrew, Loretz & Biswas, 2013). Hence, it was used to find the possible differences in learning behaviors between high performing students and low performing students in general and also within groups of students using set A or B.

To utilize this technique, collaboration with the Vanderbilt University was continued. Students' sequences of actions for all the 52 students were prepared in a similar way as done during pilot study for analysis. The parameters used by SPM that were still used for DSM algorithm to extract the students' behavior were sequence (S-) support and instance (i-) support. Similar to pilot study, in this analysis, an s-support threshold of 50% to analyze patterns that were frequent, and a maximum gap size constraint of 3 was employed. To identify the sequence of actions whose usage more clearly differ between two groups, the technique screens the s-frequent patterns based on the p-value of a t-test comparing pattern i-support between the groups. As noted by Kinnebrew, Loretz & Biswas (2013) that the t-test is not used to infer that the two groups of sequences differ but it is used as a heuristic to identify more interesting patterns: "the i-support of the pattern differs between the groups provides a useful heuristic for limiting patterns to those that are likely used differentially in the two groups" (p. 9). Thus, it focuses on finding out the patterns that are utilized more often by one group that the other.

Chapter 6: Results for the Final Study

This chapter is organized as follows. Section 6.1 includes the background information of the students. Section 6.2 describes the evaluation results of students' conceptual learning and their perceived learning value for various components of the OWLS. Evaluation of students' engagement within the OWLS is presented in section 6.3. Section 6.4 contains the relationship between students' learning and engagement. For each of these broader sections, there are sub-sections to demonstrate the results for each of the different types of learning and engagement variables. Finally, in section 6.5 the evaluation of students' experiences and challenges in completing the OWLS-based task are explained.

6.1 Background Information about the Sample

The pre and post-survey included some questions on students' background. From the pre-survey the following information is known, which is summarized in Table 6-1. Among 52 students, there were 18 females and 34 male students. For ethnicity, most of the students (43/52) were White/Caucasians, while 7 were Asians, and 2 had unknown ethnicity. Students were asked about the number of water quality course/s and the name of the course/s taken by them other than the course where the implementation was carried out. It was found out that 35 students had not taken any water quality course, while 17 students had taken one or more water quality course/s. Thus, these 17 students had some background knowledge of water quality compared to the rest of the students. From post-survey responses, it can be said that all but one of the students had not accessed the OWLS before the OWLS-based implementation. Also, all these students signed into the OWLS and have not accessed OWLS in any other way. Therefore, according to students' background information, students varied mostly according to their gender, and background knowledge of water quality. Additionally, 30 students completed set A, while 22 students completed set B of the OWLS-based task, which denotes variation in instructional design.

To support and improve the cyberlearning of diverse group of students, it is important to explore the difference in engagement and learning according to their background information. From literature it is known that males and females might experience the learning environment in different ways and thus it is useful to analyze the difference in learning and engagement according to the gender differences (Fredricks, Hofkens, Wang, Mortenson & Scott, 2018). This has been studied by handful of researchers in terms of traditional classroom engagement and rarely studies in terms of cyberlearning. In addition, prior or background knowledge is known to impact students' learning and how they tend to regulate their behavioral engagement (Stark & Lattuca,1997; Pardo, Han & Ellis, 2017). Also, in the context of technology-enhanced teaching and learning, instructional design plays an important role in the implementation of learning activities that is aimed to facilitate student learning (Wiley, 2002). Thus, these variables, gender, background knowledge and set A/B (instructional design) are considered as control variables for all the analysis related to students' learning and engagement measures.

Table 6-1. Background information about the sample

Gender	Male: 34	Female: 18	
Ethnicity	White/Caucasians: 43	Asians: 7	Unknown: 2
Background knowledge of water quality	Yes: 17	No: 35	
Number of students signed into the OWLS	52		
Set for the OWLS-based task	Set A: 30	Set B: 22	

Further, to understand the cohort in respect to their academic standing, students' self-reported GPA was compared between the groups differentiate by these control variables: gender, instructional design and background knowledge. Due to smaller sample size in each group and non-normal distribution of GPA scores, Wilcoxon Rank Sum non-parametric test was carried out to find the statistical differences by each factor. It was found that females had significantly higher GPA than males (p-value- 0.0117) at the 0.05 level of significance. For the other two variables, no significant difference was observed between these groups. This result indicates that the females in the cohort of 52 students were better performers than males.

Additionally, in both the pre and post-surveys students were asked to rate their proficiency in water quality concepts as either none, basic, intermediate, advanced or expert, which were coded as 0 through 4, respectively. Figure 6-1 shows the box plots to demonstrate the change in water quality proficiency levels of the students from the pre to the post-survey. These pre and post-survey data were paired but not normally distributed, so the Wilcoxon Signed Rank Test was carried out to test the difference between the pre and post-survey responses. It was found out that there was a significant increase (p-value < 0.0001) in water quality proficiency level of the students from the pre to the post-survey at the 0.01 level of significance. The course content covered during the time between the pre and post-test included concepts related to water quality along with the OWLS-based task. Thus, this result does not demonstrate that the increase in proficiency level of the students was only due to the OWLS-based task, but it does show that the OWLS-based task was part of course content, which made the shift in water quality proficiency level of the students from the pre to the post-survey.

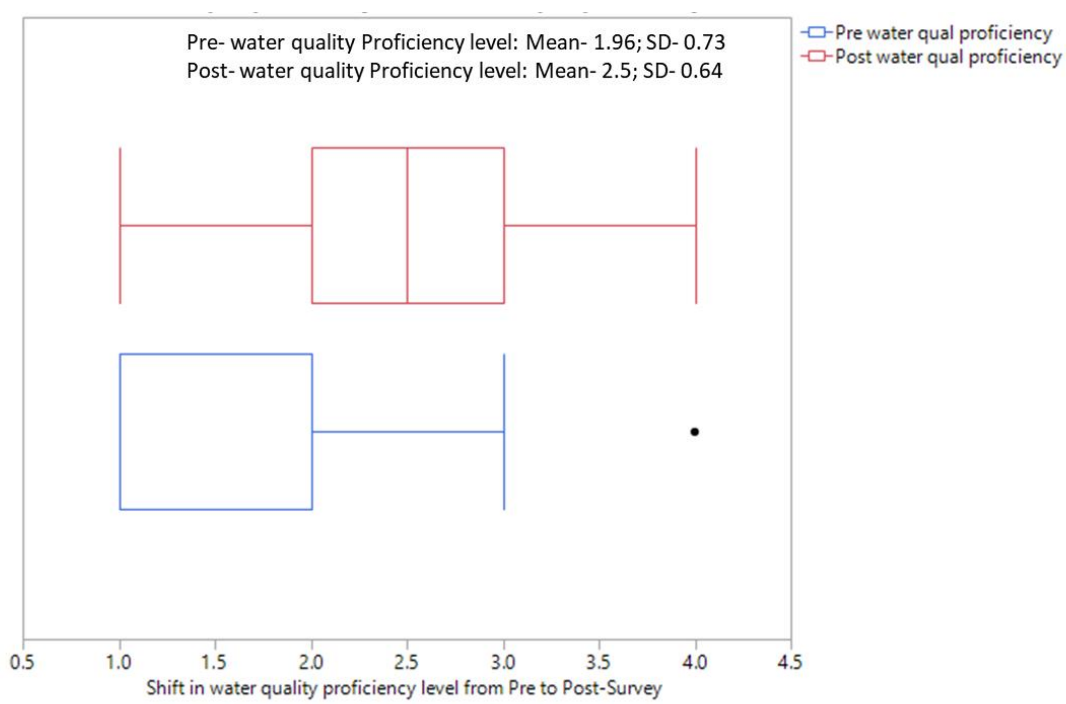


Figure 6-1. Comparison between students' proficiency levels in water quality concepts between the pre and post-survey.

6.2 Results for Research Objective 1

Briefly, this research objective evaluated individual students' learning with the OWLS by directly measuring their learning and indirectly measuring their perceived learning. Their perceived learning values for different components of the OWLS were also assessed.

6.2.1 Evaluation of Students' Conceptual Learning with the OWLS

Students' learning with the OWLS was measured directly in two ways: scores on the OWLS-based task and scores on the 9 content-based multiple choice questions asked in the pre and post-surveys. The OWLS-based task had two sets A/B and was graded out of 20 with a rubric, as mentioned in Chapter 5. To address the inter-rater reliability of the scores, the researcher and the graduate teaching assistant (GTA) of the course graded the OWLS-based task. It is found that the scores calculated by both the graders significantly and positively correlated with 0.88 Pearson correlation coefficient at the 0.01 level of significance (p-value < 0.0001), showing the high inter-rater reliability of the scores. Also, the scorers graded by the researcher significantly and positively correlated with the self-reported GPA of the students with a Pearson correlational coefficient of 0.4 at the 0.01 level of significance (p-value = 0.0033). This shows that the scores of the students on the OWLS-based task were consistent with the overall performance of the students in their undergraduate curriculum. Thus, the scores students received on the OWLS-based task were reliable to be used for further analysis.

Table 6-2 shows the descriptive statistics of the *OWLS-based task scores* with respect to the total score, and scores on the three parts (part # corresponds to Set A). The mean of the total OWLS-based task score was 17.4 out of 20, with standard deviation (SD) of 1.99 and median of 18. The SD shows that the scores were widely spread out. Comparing the mean, SD and median on the three parts of the task, it is seen that students' score was low in part 2 (Description of the Webb Branch Watershed) with higher SD compared to the other two parts. To further analyze the learning scores, the total OWLS-based task scores were compared between groups formed by the following factors: set A/B, gender and background knowledge of water quality. Due to smaller sample size in each group and non-normal distribution of data, Wilcoxon Rank Sum non-parametric test was carried out to find the statistical differences by each factor and results are shown in Table 6-3. The effect size was also calculated to find out the standardized difference between the two means as the sample size were very different, which are also present in Table 6-3. For the set A/B, it is found that students completing set B scored significantly more than students completing set A (p-value = 0.0017) at the 0.01 level of significance, and the effect size is more than four SDs. In terms of gender, male students performed significantly less than female students (p-value = 0.0795) at the 0.1 level of significance with an effect size of more than two SDs. While for students with background knowledge of water quality, performed significantly better than others (p-value = 0.0662) at the 0.1 level of significance with an effect size of more than two SDs. Therefore, students performed well on the OWLS-based task as indicated by the high mean and median value for the total OWLS-based task scores, but it significantly varied across groups formed by sets, gender and background knowledge in water quality. The gender difference can be the result of having better performing females than males in the cohort as indicated by their reported GPAs. Furthermore, among the three parts of the OWLS-based task, students performed better on parts 1 and 3, compared to part 2 of the set A. For further analysis of students' engagement in relation to their learning, students were divided into two groups according to their median score of 18: a group of *high scorers (28 students)* having score equal to or more than 18, and a group of *low scorers (24 students)* having scores less than 18.

Table 6-2. Descriptive statistics of the OWLS-based task scores

OWLS-based Task	**Total Score**	**Mean**	**SD**	**Median**
Total OWLS-based task score	20	17.4	1.99	18
Part 1 Scores (Set A): Analysis of Dissolved Oxygen and Water Temperature values	10	9.38	0.95	10
Part 2 Scores (Set A): Description of the Webb Branch Watershed	5	3.54	1.35	4
Part 3 Scores (Set A) : Benefits of continuous environmental monitoring	5	4.54	0.70	5

Table 6-3. Wilcoxon Rank Sum non-parametric test results for the total OWLS-based task scores by various factors.

Factors	**Types**	**N**	**Mean**	**SD**	**p-value**	**Effect size Hedges' g**
Set	A	30	16.78	0.33	0.0017***	4.63
	B	22	18.43	0.39		
Gender	Male	34	17.10	0.33	0.0795*	2.86
	Female	18	18.19	0.45		
Background knowledge in water quality	Yes	17	18.14	0.47	0.0662*	2.56
	No	35	17.15	0.33		

****Significant at the 0.01 level of significance; * Significant at the 0.1 level of significance*

To compare students' change in knowledge from pre to post-survey, students were asked to answer *nine multiple choice content questions (CQ)* in both the pre and post-survey. These nine questions are shown in Table 6-4. A set of three questions separated by the colors blue, green and pink, were aligned with the part 1, 2 and 3 of the OWLS-based task shown in Table 6-2, respectively. To determine the change in knowledge of the students from the pre to post-survey, paired t-test was carried out to compare the mean scores for each of the CQ before and after the OWLS-based task, and the effect size was calculated to find out the standardized difference between the two means. The results of these tests are shown in Table 6-4. It is found that seven out these nine questions had a significant increase at the 0.01/0.05 level of significance. For the first three CQs, there was a significant increase from pre to post-survey scores; however, CQ1 and CQ3 had moderate effect size compared to CQ2. The large effect size for CQ2 might be because of the fact that students were more likely to answer CQ2 after completing the part1 of the OWLS-based task (set A) than CQ1 and CQ3. For the next three questions, there was significant increase for CQ4, and not for CQ5 and CQ6. However, the effect size was very larger for CQ4, moderate for CQ5 and zero for CQ6. It should be noted that CQ6 was asked since the OWLS-based implementation was planned to cover such concept but it was not covered during actual implementation. This led students to perform similarly in the pre and post-survey, resulting into effect size of 0. Whereas, students were expected to perform well on CQ4 if they have read about the Webb Branch watershed, and perform well on CQ5 if they have read in-depth about the Webb Branch watershed while completing the part 2 of the assignment. The large effect size for CQ4 indicates that many students read about the watershed. For CQ5, through there was no significant increase from pre to post-survey, the moderate effect size shows that at least some students read in-depth about the Webb Branch watershed while completing the OWLS-based task. For the last three CQs, there was a significant increase from pre to post-survey with the moderate and small effect size for CQ7 and CQ8, respectively, and large effect size for CQ9. This indicates that probably by completing the OWLS-based task, students on average, moderately improved their knowledge on the continuous environmental monitoring system (CQ7 and CQ8), and largely improved their knowledge on the reason for high turbidity in a stream (CQ9), which can be known from a case-study within the OWLS.

Comparing these results with students' performances on each part of the OWLS-based task, it can be said that students' high means scores for part 1 and 3 are consistent with the significant increase for each of the CQs for these two parts, while comparatively low mean score on part 2 corresponds to significant increase in one out of three questions in this part. Therefore, this result clearly portrays students' improvement in knowledge from before to after the OWLS-based implementation. Correlational analyses between the OWLS-based task scores and the total 'post-pre' CQ Score gain, and the OWLS-based task scores and the total post CQ score showed no significant relationships suggesting that the OWLS-based task scores and the CQs might not be related.

Table 6-4. One-way ANOVA results for the total OWLS-based task scores by various factors

Multiple Choice Content Questions	**% correct in Pre-test**	**% correct in Post-test**	**Pre-Post Prob < t**	**Effect Size Cohen's d**
CQ1: Identify the water quality parameters that have distinct diurnal (daily) variation	47.16	69.98	0.0164**	0.43
CQ2: Solubility of oxygen is higher at 0 deg C compared to at 15 deg C	33.96	73.58	< 0.0001***	0.95
CQ3: During a summer thunderstorm the water temperature in the stream will increase	52.83	69.81	0.0243**	0.37
CQ4: The land use of the local Webb Branch watershed is best described as	7.69	64.15	< 0.0001***	1.45
CQ5: Which of the following conditions will induce high peak discharge rate of	47.16	50.94	0.4055	0.4

relatively short duration, i.e. the stream responds to events quickly and returns to base flow conditions quickly?				
CQ6: Specific Conductivity will usually ---------?---------- in the local Webb Branch watershed during a winter storm event	69.81	71.69	0.50	0
CQ7: Select among the following that are directly related to the continuous modeling of water quality parameters:	75.47	92.45	0.0093***	0.47
CQ8: Data errors from the continuous water quality monitoring station can always be attributed to environmental (natural) factors	77.35	88.67	0.0285**	0.32
CQ9: What can be the reason for high turbidity in a stream, if there is no storm event?	37.73	75.47	< 0.0001***	0.85

****Significant at the 0.01 level of significance; ** Significant at the 0.05 level of significance*

In addition, to investigate the variation of pre and post CQ scores according to the control variables, the Wilcoxon Rank Sum non-parametric test was performed with each of the total pre and post CQ scores (sum of the CQ scorers) differentiating by gender, set and background knowledge. It was found that the total Pre CQ scores did not differ by any of those factors. For the total post CQ scores, it did not differ by gender and set; however students with background knowledge performed significantly better than their counterpart (p-value 0.0166). This result indicate that all students gained knowledge in from pre to post-test without too much variation by their gender and sets, but students who had more background knowledge gained more knowledge than others.

6.2.2 Evaluation of Students' Perceived Learning with the OWLS

There were five items in the post-survey that asked students' perceptions about their learning with the OWLS on a scale of 1 to 6 from strongly disagree to strongly agree. The items (referred to as OPs) and its mean, SD and median are shown in Table 6-5. It can be observed that the means were greater than equal to 4.7/6, which means students agreed or mostly agreed that OWLS helped them to learn about the Webb Branch watershed, and the importance/purpose of continuous environmental monitoring, to analyze environmental monitoring data, to relate their theoretical knowledge to real-world water quality events happening in their local Webb Branch watershed and identify water quality changes. While formulating these questions, OP1, OP2, and OP3 were aligned with part 2, 3 and 1 of set A of the OWLS-based task, respectively. However, no significant correlation was found between students' perceptions of each of the three items with students' scores on the corresponding part of the OWLS-based task. Therefore, these results indicate that students' perceptions about their learning with the OWLS were high (~5/6) but is not related to their performance of the OWLS-based task. Further, mean perceived learning score was calculated to compare it with the total task score and the total post CQ scores, respectively. Similar to the earlier result, no correlation was found between the conceptual learning measures and the perceived learning measure. Next, the mean perceived learning score was compared across the four variables (gender, set, background knowledge and high/low score) using Wilcoxon Rank Sum non-parametric test. Results indicated no significant difference among the students in terms of their perceived learning scores. Thus, all students had a similar perception about their learning with the OWLS.

Table 6-5. Descriptive statistics of the students' perception of their learning with the OWLS

Perceived Learning Items (measured in the Likert scale of 1 to 6)	**Mean**	**SD**	**Median**
OP1: The OWLS helped me learn about the Webb Branch Watershed	5.17	0.7	5
OP2: The OWLS helped me learn the importance/ purpose of continuous environmental monitoring	5	1.13	5
OP3: The OWLS helped me know how to analyze environmental monitoring data	4.8	0.81	5
OP4: The OWLS helped me relate my theoretical knowledge to real-world water quality events happening in my local Webb Branch watershed	4.7	0.72	5
OP5: The OWLS helped me to identify water quality changes	5	0.82	5

Besides these learning measures, the post-survey included an open-ended question asking students about their opinion on learning by completing the OWLS-based task. The open-ended responses were inductively analyzed and the themes that emerged are shown in Table 6-6 (column 2). The table also lists an example student quote for each theme (column 3) to demonstrate how students have written about the themes. The themes can be categorized into: a) learning related to the concepts covered in the OWLS-based task, learning about the LEWAS, learning of skills, learning related to the local environment (column 1). Hence, students not only perceived the benefit of OWLS as indicated by the items in Table 6-4 but also found it useful in many other ways. Students found that the OWLS-based task helped them to learn about the following water quality concepts: the relationship between water quality parameters, factors affecting water quality, trends in water quality parameters. Students also learned about the Stroubles Creek and/or Webb Branch watershed, and benefits of continuous environmental monitoring, as intended by the OWLS-based task. Many students commented on the benefits of using the OWLS as it allowed them to have the accessibility of the LEWAS and its data, to gain insights from real-world case-studies, and to learn about the process of continuous environmental monitoring and measured water quality parameters. Some of the students also mentioned that the OWLS-based task helped them to gain skill in data analysis and interpretation. Additionally, some of the students by completing the OWS-based task felt fascinated by the fact that they were dealing with environment/issues that were local to them.

Table 6-6. Categories and themes of students' learning after completing the OWLS-based task

Categories	**Themes**	**Example student quotes**
Learning related to the concepts covered in the OWLS-based task	Relationship between water quality parameters	"I learned about correlations between pH, water temperature, specific conductance, and others"
	Factors affecting water quality	"I learned about … and the different factors that affect water quality"
	Trends in water quality parameters	"I learned about the watershed and how water parameters act in this watershed"
	Strobles Creek/Webb Branch	"I learned about qualitative and quantitative aspects of the Webb Branch Watershed"
	Benefits of continuous environmental monitoring of watershed	"i learned the importance of continuous environmental monitoring."

Learning about the LEWAS	Availability of LEWAS and its data	"Also I did not know that so many measurements were being recorded on campus over by the Duck Pond"
	Real-world case-studies	"I learned about the effects of water main breaks"
	Process of continuous environmental monitoring	"I learned a lot more about the different factors involved in monitoring water quality."
	Measured water quality parameters	"The multitude of things that are measured for water quality"
Learning of skills	Data analysis and interpretation	"I also learned how to access and incorporate that data into an analysis,"
Learning related to the local environment	Local	"That you can use these projects to analyze and document natural local phenomena and local water resource problems"

6.2.3 Evaluation of Students' Perceived Learning Value of various Components of the OWLS

To evaluate students' perceived learning value of different components of the OWLS, students were asked to rate each of the 14 OWLS components on a ranking scale (1 to 4) having the following levels: not valuable (1), somewhat valuable (2), valuable (3) and extremely valuable (4). Students' scores for each of the OWLS components were aggregated to find the mean perceived learning value of each of the OWLS components. Figure 6-2 shows the OWLS components in the ascending order of its perceived learning value. It is observed that students think the "Data download" and "Live LEWAS data" component of the OWLS are the most valuable features. Next, case studies, watershed summary and site map was regarded to be important. Following these features, were the overhead view/map, key components, glossary, weather/doppler radar, home page, storm view, live camera, LEWAS intro and photo index. It should be noted that the feature rankings ranged from 2.55 to 3.71 out of 4, which indicates that students felt all the components were more than somewhat valuable to almost extremely valuable. It is also seen that students perceived higher learning value of the components, which were required to be used for the OWLS-based task compared to the ones which were not required. In section

5.4.2, the relationship between these scores of the OWLS components with students' usage of these components is shown, which provides more evidence to the fact that students' perceived learning value of the OWLS component is a function of the task.

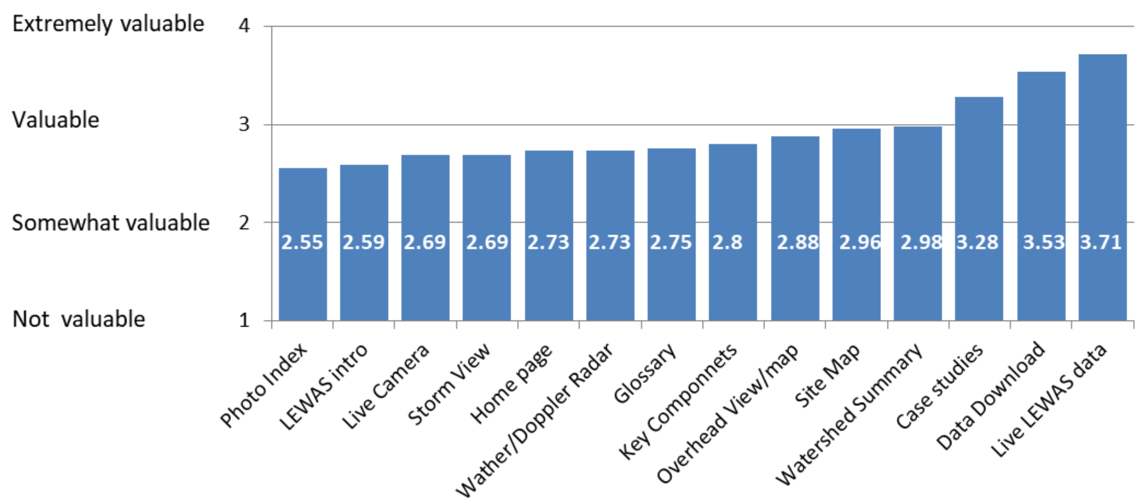


Figure 6-2 Perceived learning value of each of the OWLS components

6.3 Results for Research Objective 2

Briefly, this research objective evaluated students' engagement with the OWLS as they were completing the OWLS-based task. These include students' perceived engagement, behavioral engagement, temporal navigational patterns and resource utilization.

6.3.1 Evaluation of Students' Perceived Engagement with the OWLS

Students' perceived engagement with the OWLS was measured with the 31-item User Engagement Scale (UES). The UES was used for assessing students' perceptions towards the six attributes of engagement: aesthetics (AE), endurability (EN), felt involvement (FI), focused attention (FA), Novelty (NO) and Perceived Usability (PU). Each item is measured on a 5-point Likert scale of strongly disagree to strongly agree. It is to be noted that the AE and PU include items mostly about students' perceptions of their engagement with the OWLS interface, while the other items are related to students' perception of their engagement with the OWLS-based task/experience. First, the reliability of the survey scores was established by finding the Cronbach's alpha score for each of the engagement attributes and the entire survey. To ensure the reliability of a survey instrument, a high value of Cronbach's alpha, usually over 0.70 is acceptable (Cortina, 1993). Table 6-7 shows the number of items for each engagement attributes, with the corresponding Cronbach's alpha value and the alpha value for all the UES items. It is seen that all the alpha values ranged from 0.7 to 0.82, which determines the reliability of the sub-scales and the entire scale for measuring the perceived engagement to be acceptable.

Next, Table 6-7 also shows the descriptive statistics of the students' perceived engagement in terms of the six dimensions/attributes of engagement and the overall engagement score. The mean value for each engagement attribute and the overall engagement score was calculated as suggested by O'Brien, Cairns & Hall (2018). It is seen that mean value for all the attributes ranged from 2.91 to 3.67 out of 5. The student perceived higher usability (3.67/5) with the OWLS compared to their perception about the aesthetics of the system (2.91/5). This means that students felt that the OWLS was easy to use but, moderately agreed with the look and feel of the system. The endurability score with the OWLS-based task was high (3.63/5), followed by felt involvement score (3.44/5) and novelty score (3.23). This shows that the students found the OWLS-based experience to be moderately rewarding and involving, and provoking their curiosity. However, the focused attention score was comparatively low (2.91/5) indicating that the OWLS-based task did not draw too much students' attention. Thus, the engagement attributes varied in intensity in the context of the OWLS. Overall, the mean engagement score was 19.87 out of 30 (66.23%). The variation of the perceived engagement in terms of the overall perceived engagement score for all the 52 students is shown in figure 6-3. It is seen that except few, most of the students have perceived engagement score between15 to 25 out of 30. This shows students have moderately high perceived engagement with the OWLS and its task.

Table 6-7. Descriptive statistics and internal consistency values of the attribute of perceived engagement

Engagement Attributes	**No. of Items**	**Mean**	**SD**	**Median**	**Cronbach's**

					Alpha
Aesthetic (AE)	5	2.91/5	0.75	2.8	0.82
Endurability (EN)	5	3.63/5	0.50	3.8	0.73
Felt Involvement (FI)	3	3.44/5	0.69	3.66	0.7
Focused Attention (FA)	7	2.97/5	0.75	2.92	0.75
Novelty (NO)	3	3.23/5	0.69	3.33	0.74
Perceived Usability (PU)	8	3.67/5	0.58	3.8	0.81
Mean perceived engagement (PE)	31	19.87/30	2.83	20.14	0.79

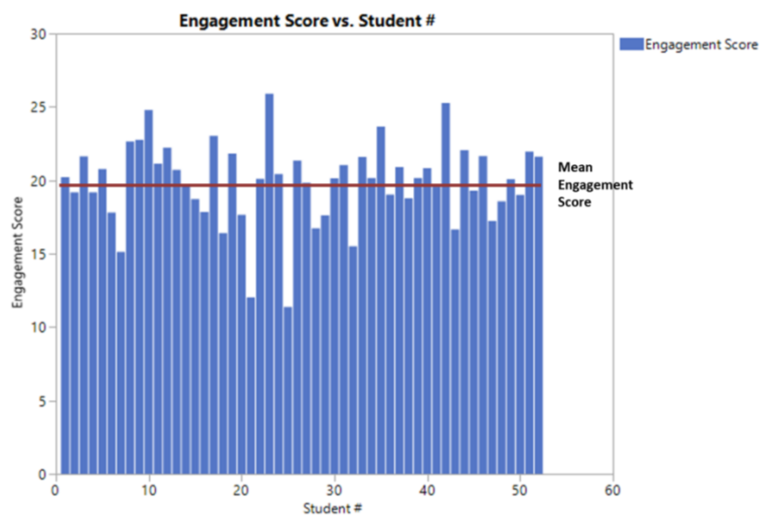


Figure 6-3. Students' overall perceived engagement scores

To investigate the individual differences in the overall engagement scores, the three factors were considered: set A/B, gender and background knowledge of water quality. Wilcoxon Rank Sum non-parametric tests were conducted and the results are shown in Table 6-8. It is seen that students' perceived engagement significantly differed by gender. Female students perceive significantly higher engagement than the male students. Also, the effect size between the males and females is very large. While the set and the background knowledge of water quality did not affect students' perceived engagement.

Table 6-8. Wilcoxon Rank Sum non-parametric tests results of the students' perceived engagement scores across factors.

Factors	Types	N	Mean	SD	p-value	Effect size Hedges' g

Set	A	30	19.65	0.52	0.8895	0.90
	B	22	20.16	0.60		
Gender	Male	34	19.24	0.64	0.0521*	3.36
	Female	18	21.24	0.46		
Background knowledge in water quality	Yes	17	20.50	0.68	0.1783	1.24
	No	35	19.56	0.47		

** Significant at the 0.1 level of significance*

6.3.2 Evaluation of Students' Behavioral Engagement within the OWLS

Students' behavioral engagement was measured by analyzing the user-tracking data. Similar to the pilot study, four measures of behavioral engagement was considered for this study. The *On OWLS time*, which is the time students spent to interact with the OWLS to complete the OWLS-based task. The *Off OWLS time* is the time that students spend on the task document to write their findings of the OWLS-based task. The *time on task*, which is the total time students have spent on the OWLS-based task. The total *numbers of clicks* students have employed on the OWLS to complete the OWLS-based task. Figure 6-4 shows the bar graph for these four measurements for all the 52 students (x-axis), where deep blue bars represent the On OWLS time, the yellow bars represent the Off OWLS times, the total height of the deep blue and yellow bars represent the time on task, and the light blue bars represent the number of clicks. The y-axis represents the time in minutes or the number of clicks, as appropriate.

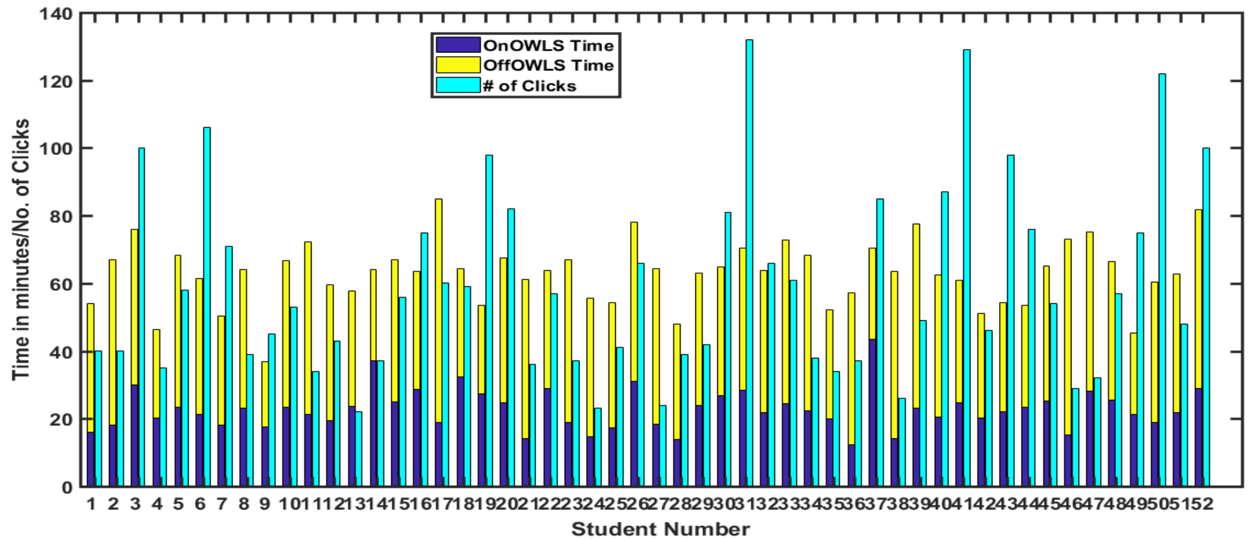


Figure 6-4. Students' behavioral engagement for the OWLS-based task

Table 6-9. Descriptive statistics and the pairwise correlation between the behavioral engagement measures

Engagement Measures	**Mean**	**SD**	**Median**	**Time on task**	**On OWLS time**	**Off OWLS time**	**Number of clicks**
Time on task	62.97 min	9.52 min	63.81 min	1.000			
On OWLS time	22.74 min	5.94min	22.25 min	0.3948 (0.0038***)	1.000		
Off OWLS time	40.21 min	9.02 min	41.03 min	0.7960 (<0.0001***)	-0.2418 (0.0842*)	1.000	
Number of clicks	59	28	53.5	0.1233 (0.3838)	0.3982 (0.0035***)	-0.1321 (0.3505)	1.000

****Significant at the 0.01 level of significance; *Significant at the 0.1 level of significance*

Table 6-9 shows the descriptive statistics and the pairwise/Pearson correlation between these four engagement measures. It is seen that on average students took almost 63 min to complete the full task. Within that time, on an average students have spent 22.74 min on the OWLS and 40.21min on the task document. To complete the task, students' mean number of clicks was 59. From the correlational analysis, it is found out that there is a significant and positive relationship between the following at the 0.01 level of significance: On OWLS time and number of clicks, time on task and On OWLS time, and time on task and Off OWLS time. Additionally, it is found that there is a small negative correlation between On OWLS time and Off OWLS time at the 0.1 level of significance. The relationship between On OWLS time and number of clicks indicates that the two types of measurement for assessing students' behavioral engagement within the OWLS, is consistent. The other three relationships bring out the facts that if both the On OWLS time and Off OWLS time increases, the time on task will increase or vice versa, however, when the time on task is constant, if students' On OWLS time increases their Off OWLS time will decrease.

To further analyze if students' behavioral engagement varies according to various factors, such as gender, background knowledge in water quality and set A/B, multiple Wilcoxon Rank Sum non-parametric tests were carried out. Table 6-10 shows all the results. It is found that the On OWLS time, the Off OWLS time and the time on task does not significantly vary among different groups for each factor. It is also interesting to find out that the number of clicks did not significantly vary among students attempting different set A/B. Therefore, these results indicate that the behavioral engagement between the two groups of students attempting the two sets respectively did not differ significantly. However, the number of clicks varied by gender of the students, and background knowledge of water quality. The males clicked significantly more number of times than females, and students, who had background knowledge of water quality, clicked less number of times compared to others for completing the OWLS-based task.

Table 6-10. Wilcoxon Rank Sum non-parametric test results for all the behavioral engagement measures by different factors

Factors	**Engagement measures**	**Factor Types**	**N**	**Mean**	**SD**	**p-value**
Gender	Time on task	Male	34	62.56	2.26	0.5639
		Female	18	63.73	1.64	
	On OWLS time	Male	34	22.81	1.02	0.8249
		Female	18	22.62	1.41	
	Off OWLS time	Male	34	39.75	1.55	0.4191
		Female	18	41.10	2.14	

	Number of clicks	Male	34	65.05	4.6	0.05**
		Female	18	48.22	6.4	
Other water quality course/s taken	Time on task	Yes	17	63.32	2.33	0.7109
		No	35	62.79	1.62	
	On OWLS time	Yes	17	23.08	1.44	0.3766
		No	35	22.23	1.01	
	Off OWLS time	Yes	17	39.51	2.20	0.8606
		No	35	40.55	1.53	
	Number of clicks	Yes	17	48.76	6.63	0.0219**
		No	35	64.31	4.62	
Set	Time on task	A	30	62.21	1.74	0.5228
		B	22	63.99	2.04	
	On OWLS time	A	30	21.99	1.08	0.2745
		B	22	23.78	1.26	
	Off OWLS time	A	30	40.22	1.66	0.9115
		B	22	40.21	1.94	
	Number of clicks	A	30	58.03	5.17	0.8241
		B	22	60.86	6.04	

***Significant at the 0.05 level of significance*

6.3.3 Relationship between Students' Perceived and Behavioral Engagement

A comparison of the perceived and behavioral engagement measures is shown in Table 6-11. Each cell represents the Pearson correlation co-efferent and the corresponding p-value for the correlational analysis between specific pair of variables. Results indicate that the On OWLS time is positively and significantly related to aesthetic attribute at the 0.1 level of significance. It is also related significantly and negatively to the perceived usability attribute of engagement at the 0.1 level of significance. Similar, positive and negative trends are observed between number of clicks, and aesthetics and perceived usability, respectively, but it was not significant. It is to be noted that the relationship was detected between the engagement variables, which are related to students' engagement with the OWLS, and not the OWLS-based task. It is also found out that the Off OWLS time is positively and significantly related to the focused attention attribute of engagement at the 0.05 level of significance. This relationship is between the engagement variables that are tied to the OWLS-based task experience. It shows that students, who used more Off OWLS time to write their task documents, tend to have better focused attention and vice versa.

Table 6-11. Comparison between the Perceived and Behavioral Measures of Engagement

Engagement measures	**AE**	**EN**	**FI**	**FA**	**NO**	**PU**	**Engagement Score**
Time on task	0.0544 (0.7017)	0.0579 (0.6836)	0.1803 (0.2008)	0.3075 (0.0266**)	0.1749 (0.2150)	-0.2228 (0.1124)	0.1470 (0.2938)
On OWLS time	0.2466 (0.0780*)	0.0689 (0.6276)	0.20360 (0.1476)	0.0060 (0.9961)	0.1349 (0.3402)	-0.2401 (0.0864*)	0.1125 (0.4273)
Off OWLS time	-0.1050 (0.4588)	0.0158 (0.9117)	0.0563 (0.6919)	0.3208 (0.0204**)	0.0958 (0.4493)	-0.0771 (0.5870)	0.0812 (0.5673)
Number of Clicks	0.1339 (0.3440)	0.0633 (0.559)	0.0026 (0.9853)	-0.0605 (0.6699)	-0.0843 (0.5524)	-0.1436 (0.3097)	-0.0190 (0.8939)

***AE**: Aesthetics; **EN**: Endurability; **FI**: Felt Involvement; **FA**: Focused Attention; **NO**: Novelty; **PU**: Perceived Usability:*

6.3.4 Evaluation of Students' Utilization of the OWLS Resources

To evaluate how students' were utilizing each of the OWLS resources, the data visualizations shown in figure 6-5 were created. These graphs represent the high and low scorers in the y-axis and the different OWLS components in the x-axis. Each circle on the graph represents the total number of clicks by each of the students on a particular OWLS component, where the radius of the circle is proportional to the total number of click on that component and is calculated as radius = log (n+1)/0.2, where 0.2 is a constant determined by trial and error with the plot as in Roy et al. (2017) and n is the total number of click. From the high scorer's graph, it can be said that these students were primarily using the following components: home page, watershed summary, case studies, data download, and live LEWAS data. Very few students used the other components, such as the glossary, key components and overhead view/map.

For low scorers, a similar trend of usage of the OWLS components is observed. However, when we compare the resource utilization of the high and low scorers, two key differences are observed. First, more high scorers seemed to use the watershed summary page in comparison to low scorers. This clearly demonstrates that students, who have missed answering the Part 2 (Set A) of the OWLS-based task, which asked students to write a description of the Webb Branch watershed, have got a lower score. Second, by spotting the utilization of the live LEWAS data (single_graph.html) by the high and low scorers it can be said that the low scorers were merely making more clicks than the high scorers. To further investigate this result, a Wilcoxon Rank Sum non-parametric test was carried out for the difference in a total number of clicks between the high and low scorers. Additionally, comparisons between low and high scorers were also done in relation to the mean On OWLS time, Off OWLS time and time on task. The results are shown in Table 6-12. It is found that the high scorers used significantly less clicks than the low scorers (p-value = 0.0310). Thus, the behavior of the high and low scorers differed significantly by total number of clicks or number of times they have accessed the OWLS resources, but not in respect to time.

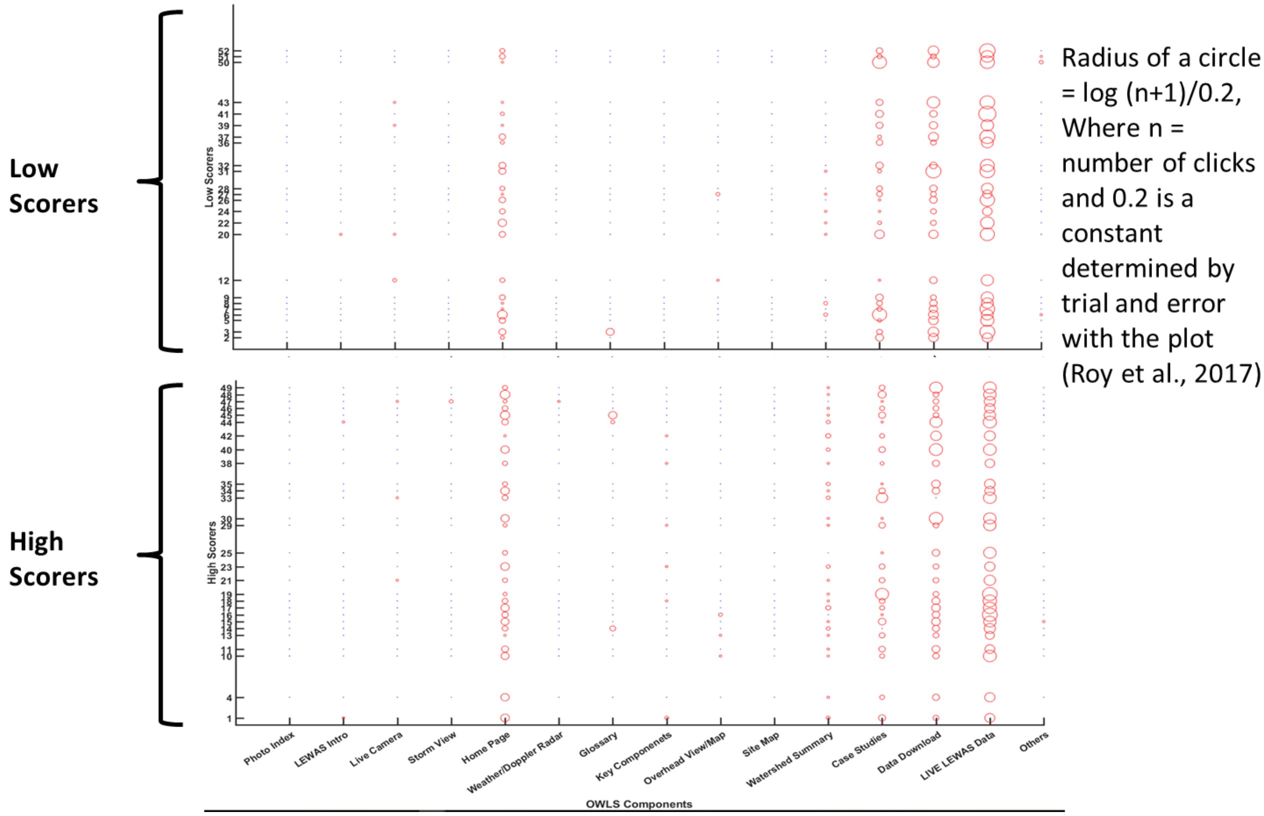


Figure 6-5. Utilization of OWLS resources by high and low scorers

Table 6-12. Wilcoxon Rank Sum non-parametric test results for all the behavioral engagement measures by different factors

Factors	**Engagement measures**	**Factor Types**	**N**	**Mean**	**SD**	**p-value**
Scores on OWLS-based task	Time on task	High	28	62.63	1.81	0.7620
		Low	24	63.35	1.96	
	On OWLS time	High	28	22.68	1.13	0.8257
		Low	24	22.81	1.22	
	Off OWLS time	High	28	39.94	1.72	0.6008
		Low	24	40.53	1.85	
	Number of clicks	High	28	50.75	5. 06	0.0310**
		Low	24	69.12	5.46	

****Significant at the 0.05 level of significance*

6.3.5 Evaluation of Students' Temporal Navigation Pattern within the OWLS

Evaluation of the students' temporal navigation was carried out to investigate different learning behaviors exhibited by the students and strategies taken by them to complete the OWLS-based task. Similar to the pilot study, visualizations were created to explore the different navigational pattern of the students. For example, figure 6-6 shows the difference in navigational patterns of the high scorers of set A and B, and low scorers of set A and B. Different colors in the graph represent different components of the OWLS, while the wider lines of a component corresponds to the On OWLS time and the thinner lines corresponds to the Off OWLS time. Since the sequence of questions was different in the two sets, the patterns were distinctly different. For instance, in part 3 of set A students were asked to write the benefits of continuous environmental monitoring by exploring the case-studies on the OWLS, while this same question was asked in part 2 of set B. Accordingly in the figure, it is seen that case-studies represented by light blue color appear at the end for set A, while it is in the middle for set B. Again, it can be seen that almost all the students were using a single browser as instructed to them during the implementation. It can also be observed from the graphs that the most used page was the single graph/ live graph page (in maroon). Also, most of the students started their task from the home/index page (in grey), except few students, such as student number 5 and 15, who started from the single graph page. These in-depth data about students' learning behavior opens up the opportunity to analyze students' behaviors in various ways.

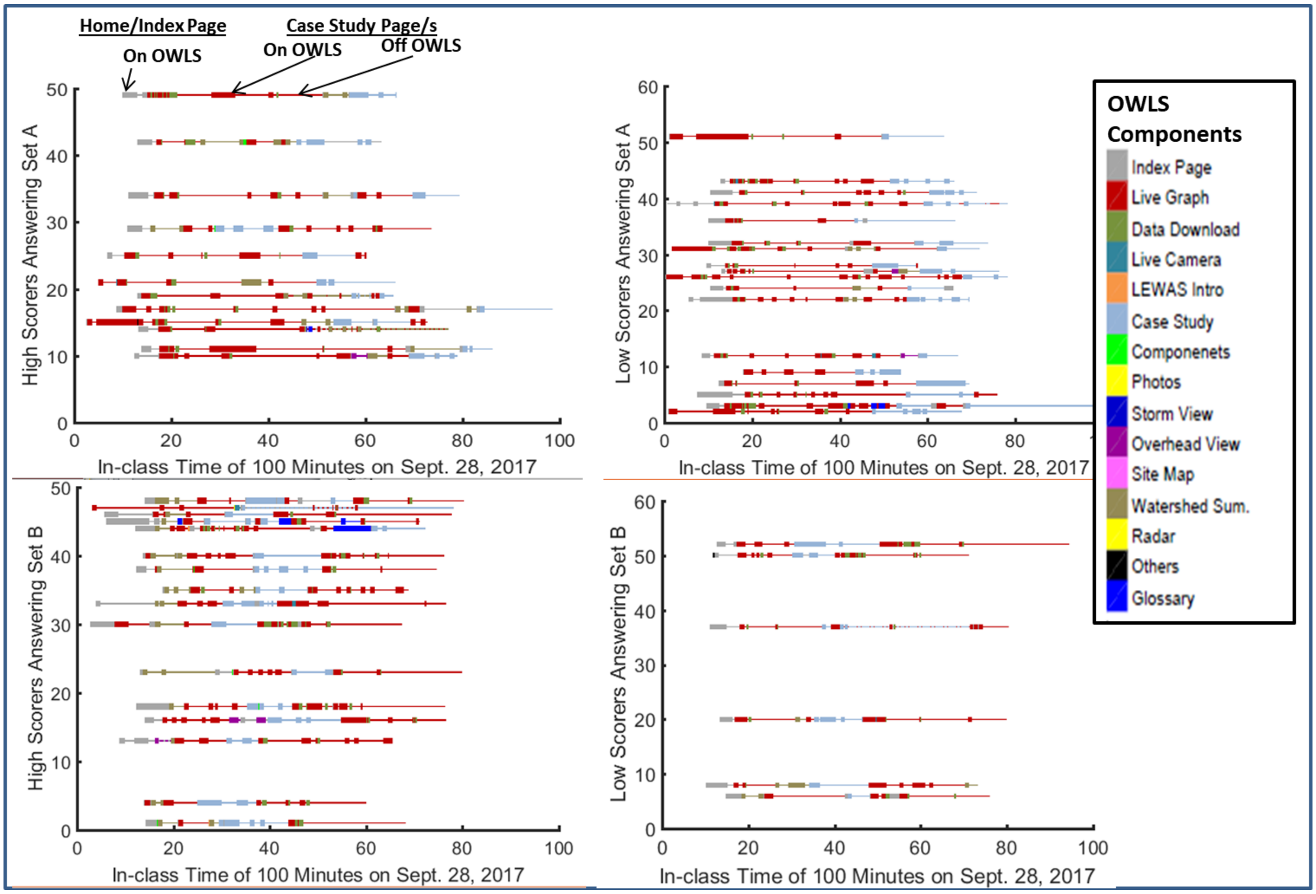


Figure 6-6. Temporal navigation patterns of the high scorers of Set A (top-left), low scorer of Set A (top-right), high scorer of Set B (bottom-left) and low scorer of Set B (bottom-right).

Application of the Differential Sequence Mining (DSM) Technique. In order to find out the patterns that were utilized more often by one group than the other, the DSM data mining technique was utilized. It was applied in four different combinations: 1) set A (A) vs set B (B), 2) all high (H) vs all low scorers (L), 3) all high scorers of set A (AH) vs all low scorers of set A (AL), and 4) all high scorers of set B (BH) vs all low scorers of set B (BL). Numerous patterns resulted from this analysis. Table 6-13 shows eight examples of differentially frequent patterns resulted from these four different categories of analysis. In this table, S-support represents the proportion of students' action sequences in which the pattern appears, and I-support is the average number of times a pattern appears in each individual student's action sequences. In this analysis, an s-support threshold of 50% was employed to analyze patterns that were frequent. A gap size constraint of 3 is used, which means a pattern might have maximum of three actions, which are not taken into account within consecutive actions in a pattern. To identify the sequence of actions whose usage more clearly differ between two groups, the technique screens the s-frequent patterns based on the p-value of a t-test comparing pattern i-support between the groups.

Table 6-13. Differentially frequent patterns detected between various groups by DSM

#	**Set A (A) vs set B (B)**	**I-Support Diff (A - B)**	**S-Support Diff (A - B)**	**S-Frequent Group**	**t-test (p value)**
1	index -> single_graph_multi -> single_graph_multi -> index -> watershed_summary -> index -> single_graph_multi -> index -> caseStudy -> index	-0.3 (0.2-0.5)	-0.5 (0.2-0.5)	B	0.0286
2	watershed_summary -> single_graph_multi -> index -> caseStudy	-0.39 (0.53-0.72)	-0.19 (0.56-0.95)	BOTH	0.0433
	All high (H) vs all low scorers (L)	**I-Support Diff (H - L)**	**S-Support Diff (H - L)**	**S-Frequent Group**	**t-test (p value)**
3	watershed_summary -> single_graph_multi -> index -> caseStudy -> single_graph_multi	0.52 (0.57-0.08)	0.57 (0.60-0.08)	H	1.0001
4	index -> single_graph_multi -> index -> single_graph_multi	0.48 (0.89-0.875)	0.02 (1.60-1.125)	BOTH	0.0332
	All high scorers of set A (AH) vs all low scorers of set A (AL)	**I-Support Diff (AH - AL)**	**S-Support Diff (AH - AL)**	**S-Frequent Group**	**t-test (p value)**
5	index -> single_graph_multi -> index -> watershed_summary -> index -> index -> index -> index -> caseStudy -> index -> single_graph_multi -> single_graph_multi -> index	0.5 (0.5-0)	0.5 (0.5-0)	AH	0.0068
6	single_graph_multi -> index -> index -> caseStudy -> index -> caseStudy -> index -> caseStudy -> single_graph_multi -> single_graph_multi -> single_graph_multi -> index	0.445 (0.5-0.055)	0.5 (0.5-0.055)	AH	0.0151
	All high scorers of set B (BH) vs all low scorers of set B (BL)	**I-Support Diff (BH - BL)**	**S-Support Diff (BH - BL)**	**S-Frequent Group**	**t-test (p value)**
7	index -> watershed_summary -> single_graph_multi -> index -> caseStudy	0.8541 (0.875-0.33)	0.875 (1.1875-0.33)	BH	0.0080
8	index -> caseStudy -> single_graph_multi -> index	0.8125 (0.9375-0.5)	0.4375 (1.3125-0.5)	BOTH	0.0131

It is to be noted that for these sets of results, the data download feature was not separated as a different action as done for the previous analysis shown in figure 6-6 and so, the single_graph in the patterns in table 6-13 includes visit to the single_garph.html page of the OWLS as well as data download action of the students, which is within the single_garph.html page in the current version of the OWLS. For set A vs set B, pattern 1 shows the sequence of actions that students, who got set B followed significantly more number of times than students, who got set A. It was interesting to see that the pattern 1 detected by the algorithm reflects the behavior of students that one can expect if students are answering part 1 and 2 of set B. Pattern 2 is common to both groups of students, set A/B, which resembles the part 1 and 2 of set B or part 2 and 3 in set A. It can be said that the similarity in sequence in instruction (1->2 or 2->3) in both the sets, have let students from set A and B perform similarly and thus, pattern 2 is common to both. For all high vs all low scorers, pattern 3 was most frequent for high scorers, while pattern 4 was common to both high and low scorers. The pattern 3 can be more frequent strategy taken by the high scorers since many low scorers missed visiting the watershed summary page for completing the task. Similarly, within each set A and B, differentially frequent patterns between high and low scorers were found out (e.g. patterns 5, 6, 7, 8). This DSM algorithm helped in identifying the patterns that are utilized more often by one group that the other. Hence this analysis demonstrates the variation in strategies by high/low scorers and instructional design (set A/B). Further, this application of data mining technique was beneficial in detecting the next step that can be taken to abstract student activities/actions into meaningful higher level categories. For example, if a single_graph page is visited but no action is performed within the page, then the action can be named as single_graph_noedit, whereas, when users interact within the single_graph page, the action can be named single_graph_edit. Similarly, a smaller time on watershed summary page can be categorized into short read while longer time on that page can be categorized into long read. In this way, the action sequences will be more meaningful for analysis. Further analysis with those sequences will be helpful distinguish the productive and counter-productive actions between high and low scorers. The inference from that analysis will be helpful to provide individualized feedback to students. In addition, these patterns identified by the DSM will be useful for improving the navigation system of the OWLS interface.

6.4 Results for Research Objective 3

This research objective evaluated the relationship between of learning and engagement. It also detects the relationship between students' perceived learning value of the different components of the OWLS and its utilization by the students.

6.4.1 Relationship between Students' Learning and Engagement within the OWLS

To find the relationship between all the engagement and learning measures, correlational analysis was carried out. Table 6-14 and 6-15 shows the correlational coefficient and p-value in parenthesis for the correlational analysis of the learning measures, with the behavioral and perceived engagement measures, respectively. Various significant relationships are found out at 0.01, 0.05 or 0.1 level of significance. First, the OWLS-based task score is negatively and significantly correlated with a correlational coefficient of -0.2746 at the 0.05 level of significance (p-value = 0.0488) with the number of clicks. This means as students' scores increased their number of clicks decreased significantly and vice versa. This result is consistent with the findings presented in figure 6-5 and Table 6-12 that demonstrates that the high scorers had significantly less average number of clicks than the low scorers. Second, the result shows significant negative correlation between the part 1 score of the OWLS-based task (analysis of dissolved oxygen and water temperature data) and the number of clicks. This explains that students, who might have clicked more for part 1 got lower scores, and vice versa. Comparing the above two results, it can be said that the part 1 of the task might have made the significant difference in the number of clicks between the high and low scoring student. Third, the mean perceived learning value of each student is significantly and positively related to their On OWLS time and the total number of clicks. As mentioned previously, the On OWLS time and the total number of clicks are two ways for measuring students' behavioral engagement with the OWLS. Thus, this result reveals that student interactions with the OWLS components are related to the way they perceive the learning value of those components. Fourth, from Table 6-15 it is found that students' perceived learning value is also positively and significantly correlated with most of the perceived engagement measures, except AE and PU. This result shows that students' opinion on the learning value of the OWLS components is associated with the experience they gain while learning with the OWLS rather than the usability and aesthetics of the system. Fifth, students' perceived learning with the OWLS is significantly and positively related to most of the perceived engagement measures except AE. In comparison, AE is significantly and positively related to the OWS-based task scores (conceptual learning). Further analysis with Wilcoxon Rank Sum non-parametric tests indicated that high scorers perceive significantly higher aesthetic of the OWLS than the low scorers (p-value - 0.0160). Therefore, students' perceived engagement is related to their perceived learning, but their perception about the aesthetics of the OWLS is related to their conecptual learning.

Table 6-14. Correlation between the behavioral engagement and the learning measures

Learning and Engagement	**Time on task**	**On OWLS time**	**Off OWLS time**	**Number of Clicks**
Perceived learning	0.0105 (0.9410)	0.0706 (0.5923)	-0.0390 (0.7839)	-0.1111 (0.4329)
Part 1 Scores	0.0006 (0.9967)	0.0526 (0.7112)	-0.0340 (0.8170)	-0.2411 (0.0850*)
Part 2 Scores	-0.1578 (0.2639)	-0.1385 (0.3276)	-0.0754 (0.5951)	-0.2206 (0.1160)
Part 3 Scores	0.0902 (0.5248)	0.0920 (0.5164)	0.0346 (0.8075)	-0.0682 (0.6309)
Total OWLS-based task score	-0.0123 (0.9308)	0.0307 (0.8291)	-0.0332 (0.8150)	-0.2746 (0.0488**)
Total Post CQ	-0.0384 (0.7868)	-0.0976 (0.4912)	0.0237 (0.8675)	-0.2275 (0.1049)
Perceived Learning value	0.1639 (0.2458)	0.3129 (0.0239**)	-0.0331 (0.8157)	0.2328 (0.0968*)

****Significant at the 0.01 level of significance; **Significant at the 0.05 level of significance; *Significant at the 0.1 level of significance*

Table 6-15. Correlation between the perceived engagement and the learning measures

Learning and Engagement	**AE**	**EN**	**FI**	**FA**	**NO**	**PU**	**Overall Engagement Score**
Perceived learning	0.1183 (0.4036)	0.5060 (0.0001***)	0.4935 (0.0002***)	0.3223 (0.0198**)	0.4513 (0.0008***)	0.2641 (0.0585*)	0.4937 (0.0002***)
WQP Part 1	0.2913 (0.0362**)	0.0007 (0.9963)	0.1978 (0.1598)	0.1266 (0.3710)	0.0926 (0.5136)	0.0093 (0.9476)	0.1841 (0.1915)
WQP Part 2	0.1183 (0.4035)	-0.2112 (0.1329)	-0.0114 (0.9359)	0.1266 (0.3710)	-0.1566 (0.2677)	0.1207 (0.3941)	-0.0385 (0.7866)
WQP Part 3	0.1361 (0.3360)	-0.2586 (0.0642*)	0.0350 (0.8057)	-0.0606 (0.6694)	-0.2404 (0.0860)	-0.1465 (0.3001)	-0.0583 (0.6812)
Total WQP Score	0.3048 (0.0280**)	-0.1985 (0.1583)	0.1469 (0.2987)	0.1229 (0.3852)	-0.1080 (0.4459)	-0.0211 (0.8820)	0.0832 (0.5575)
Total Post CQ	0.0750 (0.5974)	0.0077 (0.9570)	-0.0425 (0.7651)	-0.0323 (0.8203)	0.1336 (0.3449)	0.0801 (0.5724)	0.0514 (0.7173)
Perceived Learning value	0.2142 (0.1274)	0.4966 (0.0002***)	0.5948 (<0.0001***)	0.5400 (<0.0001***)	0.5726 (<0.0001***)	0.0472 (0.7395)	0.5846 (<0.0001***)

****Significant at the 0.01 level of significance; **Significant at the 0.5 level of significance; *Significant at the 0.1 level of significance*

6.4.2 Relationship between Students' Perceived Learning Value of OWLS Components and its Utilization

Finally, to find the relationship between the students' perceived learning value of each of the OWLS components and its utilization, Spearman correlational analysis was carried out between the perceived learning value and the total number of clicks for each of the OWLS components. Figure 6-7 shows the relationship. The relationship is found to be significant at the 0.01 level of significance with a correlational coefficient of 0.66 and p-value of 0.0095. This result is consistent with the results found in the pilot study.

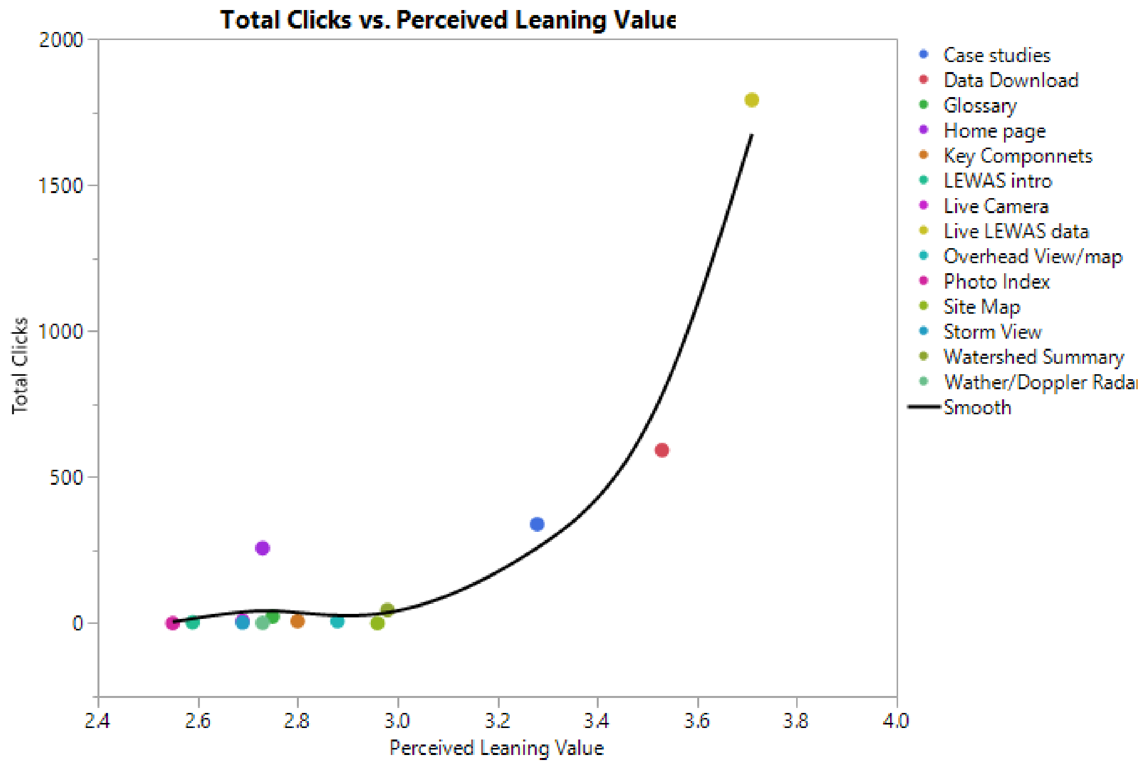


Figure 6-7. The relationship between perceived learning value of each component of the OWLS and its utilization

6.5 Evaluation of Students' Experiences and Challenges in completing the OWLS-based task

The post-survey included two open-ended questions to evaluate students' experiences and challenges in completing the OWLS-based task. All the answers were inductively coded to find the common themes. Students mentioned both the OWLS-based task and the OWLS platform as they were writing about their experiences with the OWLS-based task. However, students talked only about the OWLS when they were writing about their challenges related to the OWLS-based task. Hence, students' experiences with the OWLS-based task will be discussed followed by their experiences and challenges with the OWLS.

Overall, most students (50/52) had a positive experience with the OWLS-based task. Many students enjoyed it or had a good experience for various reasons, such as the following: understand the practical application of what they were learning in class, and connect it to the local context, understand daily occurrences, learn and gain knowledge, and found the exposure to be useful for their future. For example, one student mentioned: "*I enjoyed this project. I hope to pursue water resources engineering so what I was exposed to today undoubtedly will come up in my endeavors later*". Students also enjoyed the fact that they were learning interactively in the classroom and analyzing real-time data. One of the students said, "*I enjoyed it and prefer to participate in an interactive activity in class rather than listen to lecture*". Among these students, there were few, who showed less excitement, and used words like "*fine*", "*straight forward*" and "*cool*" to explain their experiences. In contrast, two of students found the task to be "*just another assignment*" and "*boring*", respectively. It was found that these two students were among the high scorers but their perceived engagement was quite low. Further investigation was not possible for this scenario as it was just about two of the students. The only challenge that was highlighted by three of the students was the time constraint. For example, a student said: "*I felt like the questions were somewhat vague and the website had too much content to reasonably be able to look over everything within the given time frame in a manner to fully appreciate it*".

Students have expressed both positively and negatively about the OWLS interface, and some have also provided suggestions for improvement. Some students thought that the site is easy to use, has easy navigation, has important and useful information, like case-studies and live data, and works as expected. The most common challenge was that most students were not able to access data during the training session on Tuesday. However, this issue was taken care, and many students reported that the issue was resolved on Thursday. Though, few students mentioned that they found the OWLS interface to be slow, and indicated that it took time in loading the data. This might have happened as many students were accessing lots of the data at the same time. Few students had issues with downloading the data. One mentioned that the data could not be downloaded from a MacBook browser. These technical problems are being investigated following the implementation. Apart from this, some students thought that the navigation and the look/visuals can be improved to make it more appealing to use. Some students gave suggestions for improvement, which include the addition of tutorials on introductory concepts for making it engaging to younger students, and the addition of functionality for finding averages and ranges of data.

Chapter 7: Discussion & Conclusion

This study had two goals: 1) advancement of the Online Watershed Learning System (OWLS), and 2) investigation of personalized learning and engagement within the OWLS for environmental monitoring education. To accomplish these goals, a pilot study followed by a final implementation of the study was carried out. In this chapter, the author reflects on the key findings of this research and presents the important conclusions. Limitation of the study, implications of the study and directions for future research are discussed at the end.

7.1 Advancement of the OWLS

Addition of the user-tracking system. To advance the OWLS, a full-stack development of the user-tracking system was achieved following the client-server architecture. The OWLS now includes a login system to identify individual users across devices and has tracking functionalities for detecting each user's interaction with the OWLS as shown in figure 7-1. Compared to the many existing user-tracking systems that only record users' requests on the server-side, this system tracks users' actions on the server-side as well as on the browsers or client-side (May & George, 2011). 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 information (e.g., the name of the environmental parameter chosen, dates chosen, etc.). May & George (2011) stated that these types of tracking data enable researchers to get a detailed description of the users' sequences of actions with the computer-mediated interfaces to fulfill a certain task. Thus, these features were beneficial in this study as to investigate students' personalized learning and engagement for an OWLS-based environmental monitoring task. A relational PostgreSQL database, called owlsusers is used in this user-tracking system to securely store all users' login and user-tracking information along with the corresponding timestamp in two tables in the LEWAS server, respectively. This makes the OWLS a secure learning environment for the users and addresses the concern of protecting sensitive personal data within a cyberlearning system (May & George, 2011). Moreover, to build students' trust with the OWLS, consent was taken from the study participants before analyzing their user-tracking data. The user-tracking system also detects and stores the operating system, device type and the browser information of each user's computer used to access the OWLS. This provides evidence that the user-tracking system is compatible with several browser types, operating systems, and device types without installation of any additional software. By presenting the computational architecture and functionalities of the secure individualized user-tracking system of the OWLS, this study informs literature about the distinctive technologies that often creates a barrier for implementing technologies in educational settings (Liu, Calvo, Pardo & Martin, 2015).

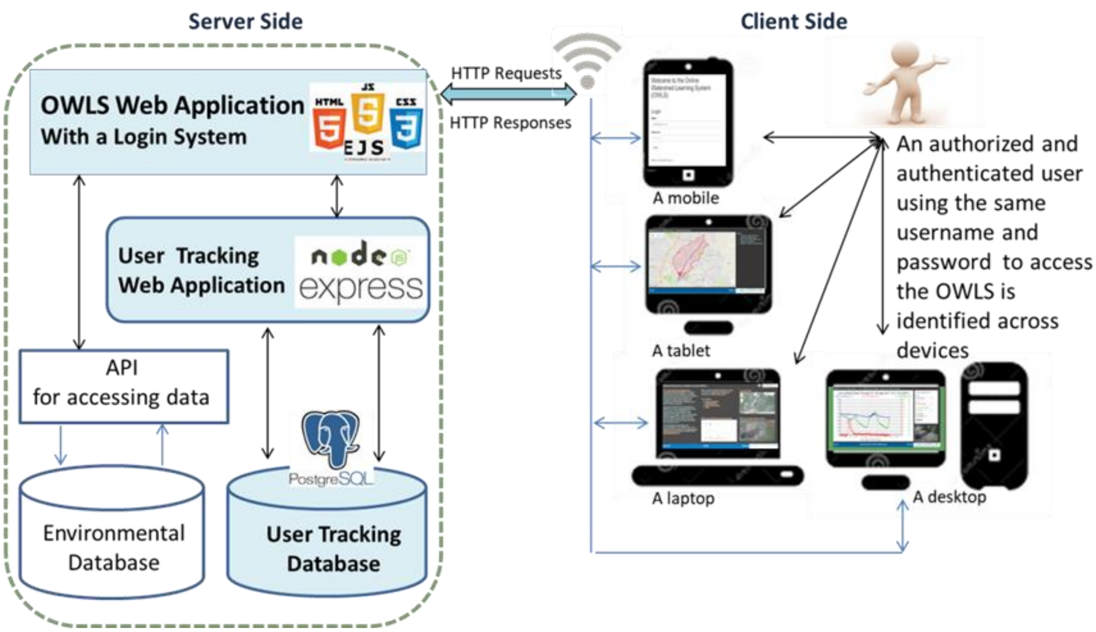


Figure. 7-1. The architecture of the OWLS user-tracking system.

Understanding personalized student learning. The study implementations were effective in testing out the potential of the user-tracking system in understanding how each student engaged with the OWLS for learning environmental monitoring concepts. Figure 7-2 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 the OWLS-based environmental monitoring task shown in Appendix B.E. 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 the three parts of the task. It also shows the time when students went off the OWLS and when they come back to work on the OWLS.

This clearly portrays that the user-tracking system has advanced the research potential of the OWLS in the context of personalized learning. Therefore, one of the contributions of this research is this user-tracking system, which will be beneficial in any future research agenda involving understanding individual students' learning with the OWLS.

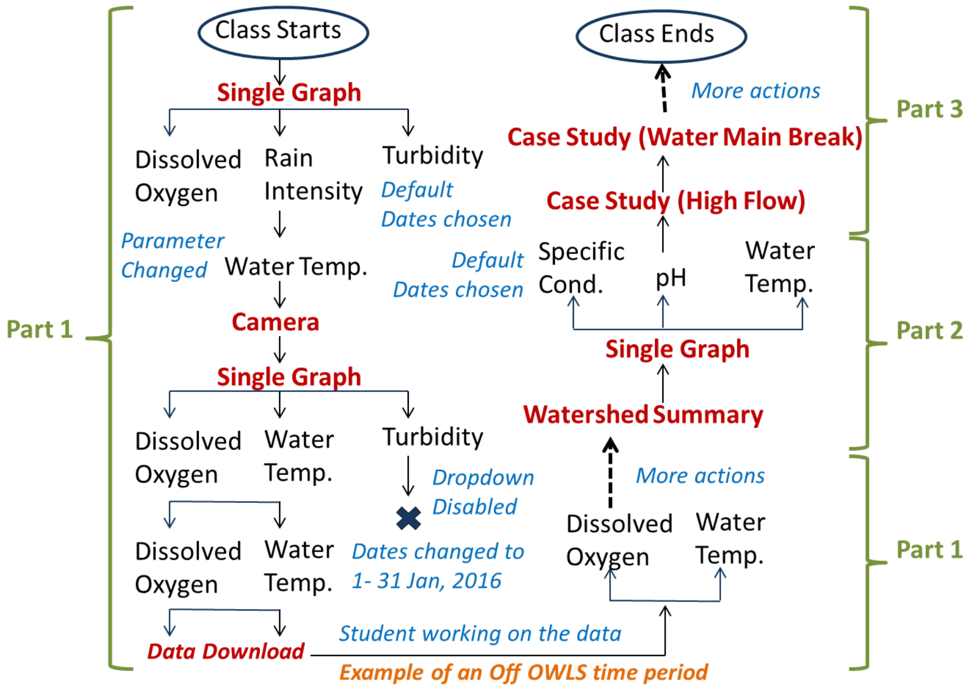


Figure. 7-2. An example of sequence of actions derived from the user-tracking system of a student completing the OWLS-based task having part 1, 2 and 3.

Addressing limitation of the Google Analytics-based user-tracking. This user-tracking system addresses several limitations of the Google Analytics-based user-tracking system. First, by detecting the user-tracking data at client and server-side, the browser type, operating system, and device information at an individual level, this user-tracking system addresses limitations of the Google Analytics-based user-tracking system used with the earlier version of the OWLS that could only detect group of users' action on the server-side (Brogan, 2017). Additionally, compared to the Google Analytics-based system that could only record the time of the last OWLS page visited by a user, this user-tracking system is able to record a user's exact logout time from the OWLS. The user-tracking system also includes a unique feature for detecting whether a user is actively using the OWLS browser or not using it. This feature allowed estimating the total On OWLS time and total Off OWLS time in this study. It also helps in identifying the time when users go offline with their browsers open at the end of the session by recording a big time difference in the database. Thus, this feature helps in the effective estimation of engagement time overcoming the limitation of logging out users after a fixed interval of time in the middle of their interaction, which was an approach taken in a study to calculate the engagement time (Baltierra et al., 2016). Also, it is better in comparison to another MOOC related study, where engagement time was measured by taking the time difference between two subsequent clicks, which were greater than 10 sec and less than 30 minutes apart (DeBoer, Ho, Stump & Breslow, 2014). Additionally, after the pilot implementation, a comparison was done between the On OWLS engagement time calculated by the Google Analytics-based user-tracking system and this newly developed user-tracking system. The results showed that for all the students the Google Analytics-based user-tracking system over-estimated the On OWLS time. This is because Google Analytics only records the time when a student visits a webpage and does record the time he/she left the webpage. 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.

From the learning analytics literature, it is known that google analytics is an easy tool that is often integrated to online learning technologies for capturing students' actions (Liñán & Pérez, 2015; Baltierra et al., 2016). 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 (DeBoer, Ho, Stump, Breslow, 2014).

Detecting factors associated with students' perceived learning value of the OWLS components. Advancement of the OWLS also included the addition of data visualization and availability features. Earlier studies with the OWLS showed that the students' perceive the highest learning value of the data availability and visualization components of the OWLS (Brogan, 2017). During the pilot and final implementation of this study, a similar evaluation of the OWLS components was carried out to understand students' perceived learning value of the OWLS components. Two groups of students accessed the OWLS for a similar amount of time in class to complete a similar OWLS-based task. The students in the pilot test had used OWLS for a previous assignment, and thus were more familiar with the OWLS. In comparison, the students in the final implementation were introduced to the OWLS during the training session, two-days before the OWLS-based task. The comparison of the results are shown in Figure 7-3. It is seen that students from both the implementations, perceived highest learning value of the Live LEWAS graph and then the data download component, which were among the data visualization and availability components of the OWLS. This result is consistent with the previous evaluation of the OWLS (Brogan, 2017).

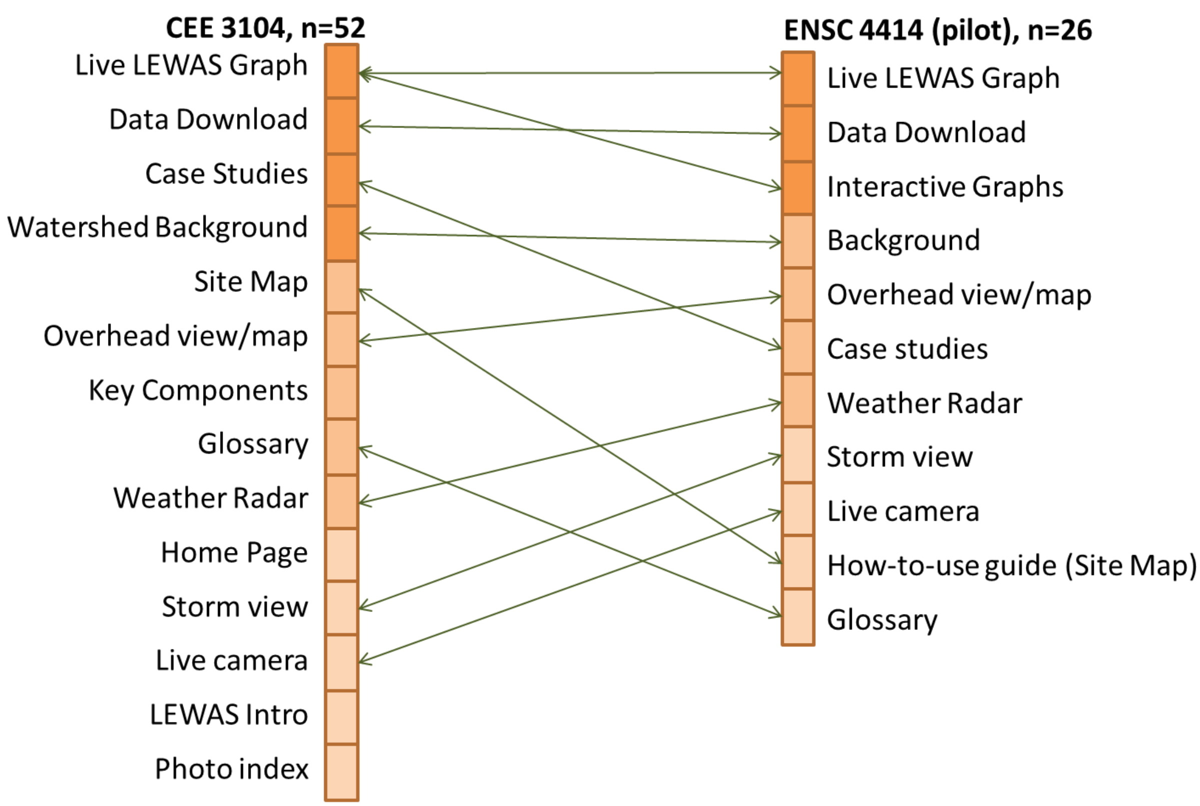


Figure. 7-3. A comparison of learning value of the OWLS components as ranked by the students of the pilot and final implementation.

Additionally, for case-studies, students from final implementation perceived higher learning value than students from the pilot implementation. This might be the effect of mandating students to go to case-study page for answering a part of the OWLS-based task during the final implementation. Watershed background page and the Overhead view/map page was ranked similarly by the students from both the classes. But it is seen that the glossary and site map pages, which were ranked low by student of the pilot class, were ranked higher by the students of the final implementation. These pages had information for operating the OWLS. Students in the final implementation, who were not much familiar with the system might have valued these pages as it was helpful for them for navigating within the OWLS . Weather Radar, storm view and camera, which were ranked generally lower than the other components, ranked comparatively higher by the pilot implementation students than the final implementation students. The reason for lower rank may be because these components were not much used by the students in both the implementations but students in the pilot implementation might have used it for their earlier assignment, which led them to rank these components higher than the pilot implementation students. It is to be noted in this context that these components were among the data visualization and availability components, but were ranked lower than the rest of the data visualization and availability components, which is contrary to earlier study with the OWLS (Brogan, 2017). Thus, this result and the comparison between the pilot and final implementation results indicate that the students' perceived learning value of various components of the OWLS is more likely to be related to the requirements of the OWLS-based task and their familiarity with the system. There is not much evidence to support the later but there are several evidences to say that students' perceived learning value of various components of the OWLS is related to the task requirements. For instance, the results from the final and pilot studies show that students' perceived learning values of various components of the OWLS is positively and significantly related to students' utilization of those components. Also, in-depth investigation of individual students' resource utilization, demonstrates that the resource utilization aligns mostly with the particular task requirements. Additionally, results show that perceived learning value of different components of the OWLS is positively and significantly correlated to the On OWLS time and total number of clicks. All, these results highlight that the students' behavioral engagement or the way students interact with the OWLS has a positive relationship to the way they perceive the learning value of the OWLS components. Thus, the earlier study with the OWLS were able to show the ranking of the various components of the OWLS, which led to the design decision of adding more data visualization and availability feature of the OWLS during this study. However, this study, by including in-depth assessment of individual students' behavioral data led to identification of factors that are associated to students' perceived learning value of various components of the OWLS from the instructional perspective (task requirements), and students' perspective (their familiarity with the OWLS), as well as from their behavioral perspective (On OWLS time and total number of clicks). This result has implication for adopting the design of a cyberlearning system according to its usage in various learning environments. Also, it demonstrates that if a study is concerned with evaluating a cyberlearning system or any other computer-mediated system, the researchers need to design activities that engage users to utilize all of the components of the system equally. Else, evaluation will be biased by the system components, to which the users are exposed.

7.2 Students' Learning with the OWLS

The first research objective of the second goal of this study was to investigate individual student's learning with the OWLS. The conclusion is drawn from all the evidence found from the direct and indirect measurements of the student learning.

Students' learning evident from multiple choice questions. Out of nine content-based multiple choice questions that were aligned with the concepts covered in the OWLS-based environmental monitoring task, students had a significant increase in score for seven of those questions from pre to post-survey. In addition, moderate to large effect size was calculated for eight of the questions. The question that had no increase in effect size was not related to the OWLS-based task. These results support the claim that students gained knowledge in environmental monitoring from pre to post implementation of the OWLS during the final study. Though, it cannot be said that the gain was only because of the OWLS-based implementation as some water quality concepts related to dissolved oxygen and water temperature was covered in the class during the time. However, it can be said that OWLS-based implementation was one of the reasons for such gain in knowledge as the multiple-choice questions were mostly tied to the content of the OWLS. This result is also supported by the result that shows students had a significant increase in their proficiency level in water quality concepts from the pre to the post-survey. Additionally, it is found out that students with background knowledge, although performed similarly like their counterpart in the pre-survey, they performed better in the post survey.

Students' learning evident from the OWLS-based task. Moreover, students on an average performed well on the OWLS-based task (17.4/20) with high variability of scores among the students. Similar results were found during the pilot study. Moreover, during final implementation, it is found that the scores significantly differed by various factors. For example, students accessing set B performed better than set A. Set B had questions in the increasing order of Bloom's taxonomy: part 1 related to understand/describe the knowledge, part 2 related to apply/ interpret the knowledge, and part 3 was related to analyze/compare the knowledge. The sequence for set A of the OWLS-based task was parts 3, 1 and 2. It was found that students performed better when instructions were in increasing order of Bloom's taxonomy. This result has implication for designing/organizing instructions/tasks in an effective way. Results also showed that female students performed better than male students, and students, who had background knowledge in water quality performed better than the other students. The result related to gender difference can be explained with the fact that the female students in the cohort were better performers than the male students as indicated by their self-reported GPA. However, the result related to the students' background knowledge affecting their performance, confirms to the fact in the literature that highlights the critical role of prior knowledge on students' learning (Stark & Lattuca,1997).

Students' learning evident from the indirect measurements. Students' perceptions of their learning constitute the indirect measurements of students' learning. It is found that students on average mostly agreed (~5/6) about their learning with the OWLS. Additionally, it is found that all students had similar perception about their perceived leaning as it did not vary according to the gender, set or background knowledge. Similarly, students from the pilot study more than agreed (5.27 /6) that OWLS help them to learn environmental monitoring concepts. Moreover, students' open-ended responses revealed that students not only learned the concepts that were covered in the OWLS-based task, they also gained knowledge about the LEWAS, they gained skills in data analysis and interpretation, and they gained awareness of their local environmental problems by completing the OWLS-based task.

Conclusion. Several pieces of evidence were found to support the claim that OWLS increased students' learning of environmental monitoring concepts. Earlier studies with the OWLS have shown that students' learning gain might be caused by the use of LEWAS, rather than the OWLS alone (Brogan, 2017). To address this limitation, this study relied on data collection utilizing only the OWLS as a cyberlearning tool within a classroom environment and did not include any LEWAS-based learning activity. Therefore, one of the contributions of this study is that it demonstrates students' learning gain with only the OWLS. Also, this study demonstrates that the students' learning with the OWLS differs by instructional design, gender and background knowledge of water quality. But, these results need further investigation to find the consistency of the results. One of the primary reasons for that is the disproportional and small sample size of each of the comparison groups in this study.

7.3 Students' Engagement within the OWLS

The second research objective of this study was to investigate individual students' engagement with the OWLS. To measure both the behavioral engagement and psychological state of students' engagement, the user-tracking data and the self-reported data using UES items were collected, respectively. The insights gained from these data are summarized under each sub-heading.

Students' perceived engagement. Consistent with the process model of engagement (O'Brien & Toms, 2008), students' perceptions about the engagement attributes varied in intensity in terms of their experiences with the OWLS. It is found that students' perceived usability with the OWLS was higher than their perception towards the aesthetic of the system. Evidence supporting this result was found from the open-ended answers, where students mentioned that they found the OWLS easy to use but its aesthetic needs improvement. For example, a student said “*OWLS was very easy to use*”, while another student said “*I think it needs better visual displays*”. In addition, students’ perception towards their felt involvement, novelty and endurability attributes of engagement was moderately high (greater than 3.2/5). Almost all the students’ positive reactions about their experiences with the OWLS found in the open-ended responses provide supporting evidence for this result. In contrast, the focused attention attribute of engagement had a low score as students felt less immersed in the OWLS-based experience. Students might have felt in this way since they had to keep track of time to finish the OWLS-based task within the class time. If students were given unlimited time, students might have felt more involved in the task. The constraint of time was also highlighted in the qualitative responses as one of the challenges for the students to complete the OWLS-based task. Utilizing the UES, the study is able to demonstrate the variation in engagement perceived by the students in terms of the different attributes of engagement, which contributes to the overall evaluation of their experience with the OWLS. The intensity of the engagement attribute might vary differently if the OWLS-based task is designed as a homework assignment. It was found that on an average, students’ overall perceived engagement score was 19.87/30. Investigating individual differences, it was found that female students have significantly higher perceived engagement than males, while there was no difference in terms of set A/B or students’ background knowledge.

Students’ behavioral engagement. The measurement of behavioral engagement of the students, while they were completing the OWLS-based task provides the following insights. First, this study showed that behavioral engagement within the OWLS can be approximated with the On OWLS time and the total number of clicks, while the Off OWLS time and the total time of task represent the engagement of the students for completing the task document and the OWLS-based task, respectively. Second, similar to the pilot study finding, the final implementation results showed a significant correlation between the On OWLS time and the total number of clicks. This provides evidence to the fact that both the behavioral engagement measures were consistent. Additionally, a significant relationship was found out between the total time on task with the On OWLS time and Off OWLS time, respectively. This result indicates the relationship between these three measures. Third, to find individual differences in behavioral engagement in terms of these four variables, several t-tests were carried out. It was found that in terms of all the engagement time there was no differences in terms of set A/B or gender or background knowledge in water quality. However, significant differences were found with the number of clicks. For gender differences, males used significantly more number of clicks than females. Students with background knowledge in water quality used significantly less number of clicks than others. This may be because students with less knowledge on water quality concepts were exploring the site more to learn and answer the task questions. But, no difference was found between the students, who answered set A/B. Fourth, it should also be noted that although the On OWLS time and total number of clicks were related, it was not sufficient to only account for the engagement time. The study shows that the total number of clicks, which indicates the amount of OWLS resources utilized by the students, was important for measuring behavior engagement as it highlighted differences in terms of students' gender and background knowledge.

Implications about students' engagement. Inferring from the perceived and the behavioral engagement measures, it is found that the engagement did not differ for the students answering either version of the OWLS-based task (set A/B). Comparing this result with students' conceptual learning, it is seen that the instructional design of the OWLS-based task relates to students' learning but not engagement within the OWLS. In terms of students' background knowledge, it did not impact students' perception of their engagement but influenced the way they actually interacted with the system to learn. This result confirms the fact that students with prior knowledge tend to plan and regulate their learning more often than students with less prior knowledge (Pardo, Han & Ellis, 2017). In terms of gender, female students had higher perceived engagement than males, while males used significantly more number of OWLS resources than females for the OWLS-based task. This study contributes by identifying the differences that exist in students' perceived and behavioral engagement with cyberlearning tools due to students' inherent properties, which according to the authors' knowledge have not been explored before. However, more investigation needs to be done to generalize these findings and to find the cause of such differences. Especially, more research needs to be done related to variability in engagement due to gender differences.

Identification of Students' temporal navigation pattern. Drawing data visualizations of the temporal navigation pattern of the individual students showed the various strategies taken by students to complete the OWLS-based task along with their progress with time. From the graph that showed the actions of 15 students engaged during the pilot study, it was found that multiple students were using more than one browser for accessing the OWLS. This led in mandating students to use one browser for the OWLS-based task during the final study. These visualizations showed students' strategies in solving the task, which often remains hidden when students complete tasks in a traditional classroom environment. This demonstrates that the OWLS-based task conforms to the situatve theory of learning, which allows students to traverse their own learning path for completing a task (Johri & Olds, 2011).The sequences of actions taken were visibly different for students answering set A and B of the OWLS-based task. Thus, this study was able to bring out the fine-grained differences that exist in students' engagement or learning process within a cyberlearning system. Further investigated in these data will help in extending the research related to advancing personalize learning, and hence, contributing more towards the grand challenge.

Application of data mining techniques. With an aim towards the direction of getting more insight from the action sequences of students completing the OWLS-based task, the data mining techniques, like sequence pattern mining (SPM) and Differential Sequence Mining (DSM) were applied for analyzing the pilot and final study results, respectively. The SPM was able to detect the frequent actions pattern taken by the pilot study students, while the DSM was able to identify the difference in strategies between two groups of students. Further, these patterns also indicate that the instructional design of the task is an important consideration for designing cyberlearning experiences for students. These results also have implication for improving the navigation system of the OWLS according to the paths followed by the students. The DSM results also showed that next step has to be taken to abstract student activities/actions into meaningful higher-level categories, which can be analyzed to identify the productive and counter-productive learning behavior of the students. Such results have the potential to close the loop of understanding individualized students' learning and then providing them with useful feedback on actions they might want to choose for improving their learning.

Detection of Students' engagement processes. A comparison of the perceived and behavioral engagement measures was carried out to get a clear picture about students' psychological and behavioral engagement in the context of the OWLS. Results indicated that the On OWLS time is positively related to aesthetic attribute and negatively related to the perceived usability attribute of engagement. It was interesting that the relationship was detected between the engagement variables those are related to students' engagement with the OWLS, and not the OWLS-based task. From the results it can be inferred that students, who liked the aesthetics of the OWLS tend to spend more time than others. And, students who had found the OWLS easy to use or had higher perceived usability used the OWLS quickly taking less time than others. According to the process model of engagement, aesthetics is associated with the period of engagement and usability is associated with the point of disengagement (O'Brien & Toms, 2008). This means that students perceiving higher aesthetics of the OWLS will sustain their engagement with the OWLS, while students perceiving higher usability of the OWLS will quickly finish their task and leave the system. Similar, positive and negative trends are observed between number of clicks, and aesthetics and perceived usability, respectively, but it was not significant. This trend needs to be investigated with bigger sample size in a future study. It is also found out that the Off OWLS time is positively and significantly related to the focused attention attribute of engagement. This relationship is between the engagement variables that are tied to the OWLS-based task experience. It shows that students, who used more Off OWLS time to write their task documents, tend to have better focused attention and vice versa. Therefore, this study is able to show to some extent that different perceived engagement attributes are tied to students' behavioral engagement in different stage of the task completion. Thus, depicting engagement as a process where various attributes of engagement are inherent at different phases of the process as shown in the process model of engagement (O'Brien & Toms, 2008). Although, the study could not demonstrate all the engagement attributes associated with point of engagement, engagement, disengagement and re-engagement, it is able to demonstrate the perceived and behavioral engagement variables those are associated with different stages of a given task. Thus, the study confirms that analyzing user's behavioral engagement along with their perception towards their engagement provides a holistic picture of students' engagement with a computer-mediated interactive system, like the OWLS. This result has useful implications in a technology-enhanced curriculum or online education that aims to engage students in various learning activities.

7.4 Relationship between Students' Learning and Engagement

To investigate the relationship between students' learning and engagement, multiple correlational analyses were carried out considering the total number of students as well as by dividing the students into high scorers and low scorers. The following conclusions are derived.

Students' behavioral engagement and learning. Correlational results between the perceived learning and conceptual learning with the behavioral engagement measures provided the following conclusions. First, an inverse and significant relationship was found between students' learning score on the OWLS-based task and the total number of clicks. These inverse trends were also observed during the pilot study, but it was not significant. It is also found that high scorers used significantly less number of clicks than low scorers. Additionally, scores on part 1 of the task, which asked students to analyze water temperature and dissolved oxygen data, varied inversely with the total number of clicks. For this part of the task, students accessed the live graph page and the data download functionality of the OWLS. Looking into the resource utilization by high and low scorers, it is seen that low scorers utilized these two features much more than the high scorers. These results show evidence to support the conclusion that in the context of the OWLS, that the conceptual learning of the individual students are inversely related with behavioral engagement in terms of total number of clicks or students' resource utilization, and the part 1 of the task is one of the major contributors in bringing out this relationship. This study identifies this relationship between learning and behavioral engagement in the context of the users and their task completion with a cyberlearning system and provides sufficient evidence to conform to the fact that engagement is "context and user dependent" (O'Brien & Cairns, 2016, p. 8). And, for the same reason, unlike many studies that show a positive relationship between engagement and learning (Ramos and Yudko, 2008; Giesbers, Rienties, Tempelaar & Gijselaers, 2013), this study depicts an opposite relationship. However, no relationship was found between the way students perceived their learning with the OWLS and their behavioral engagement. This shows that students' thoughts on their learning outcome with the OWLS are independent of how they have interacted with the system.

Students' perceived engagement and learning. Various relationships were found out by correlating students' perceived learning, conceptual learning and perceived learning value of the OWLS with their perceived engagement. Results show that students' perceived learning is positively and significantly related to five out of six attributes of perceived engagement, namely endurability, felt involvement, focused attention, novelty and perceived usability. In contrast, these attributes have no relationship to the conceptual learning measures. While, the sixth attribute, aesthetic is positively and significantly related to the conceptual learning (OWL-based task score) and the part 1 score of the OWLS-based task, respectively. It is also found that high scorers have a significantly better perception about the aesthetics of the OWLS than the low scorers. Also, the perceived overall engagement score is positively and significantly related to perceived learning. These results indicate that students' perception of their engagement attributes has a relationship to their perception about their learning with the OWLS, while aesthetic is related to how they are actually performing on the OWLS-based task. Finally, results demonstrate that students' perceived learning value of the OWLS components are significantly related to students' perception on the endurability, felt involvement, focused attention and novelty with the OWLS-based experience. Also, students' perceived overall engagement score is significantly related to their perceived learning value of the OWLS. Thus, there is a relationship between students' perceived engagement and their perceived learning value for the OWLS components. This study provides insights into the complexity and interplay between variables related to students' learning and their perceived engagement. Future studies with bigger sample sizes are required to generalize these results and find models related to students' learning and engagement.

7.6 Summary of the Contributions

In this section the key contributions of the study in terms of the literature are presented. First, this study demonstrates personalized learning and engagement within a cyberleraning system for environmental monitoring education. Although, there have been several attempts to investigate individualized student learning in the field of learning analytics and educational data mining, it is a unique contribution in the context of environmental monitoring education related to a small urban watershed (Kinnebrew & Biswas, 2012; Branch & Butterfield, 2015; Baltierra et al., 2016). Second, this study identified a better measure of engagement time by combining a logout functionality with a unique feature in the newly developed user-tracking system of the OWLS that detects at a regular interval of time whether a user is using a cyberleraning system or not. In prior studies, time spent on a task has been regarded as a measure of behavioral engagement and as a variable that is difficult to measure (Baltierra et al., 2016; DeBoer, Ho, Stump, Breslow, 2014). However, the measurement of engagement time in this study is proven to addresses the overestimation of engagement time measured by a google-analytics based user-tracking system and is believed to be a more realistic approach to measure engagement time in comparison to several methods utilized in literature, such as logging out users in the middle of a task after certain interval of time, and considering time difference between two consecutive clicks. Third, the results of this study indicate that students' perceived learning value of different components of a cyberlearning system is a function of the task that is designed based on the cyberlearnin system. The task requirements direct students to utilize certain components of the system more compared to the others, which lead students to perceive learning value of the components according to its usage. This finding suggests that for unbiased evaluation of cyberlearning systems, tasks need to be designed that lead users to utilize all components of the system. Fourth, the study confirms that cyberlearning and its task (material context) that has been designed utilizing situative theory of learning helped students to learn environmental monitoring concepts. Also, as highlighted in the theory, this study is able to demonstrate that students choose their own learning paths/strategies as observed from their temporal navigational patterns for completing the environmental monitoring task. Further, this study shows that students' strategies differed by instructional design and learning scores (Newstetter & Svinicki, 2014). These patterns can be further analyzed to provide personalized feedback to students. Fifth, in terms of engagement theory, this study indicates that measurement of behavioral engagement and perceived engagement was necessary to understand students' engagement with a cyberleraning system in a holistic way. Several relationships were found between the different measures of behavioral and perceived engagement, and also between engagement and learning variables, portraying the complex interplay of these variables within a learning environment. The findings provide sufficient evidence to conform to the fact that engagement is "context and user dependent" (O'Brien & Cairns, 2016, p. 8). Additionally, this study demonstrates to some extent that different perceived engagement attributes are tied to students' behavioral engagement at different stage of a task completion. For example, aesthetics and perceived usability are tied to the On OWLS time whereas focused attention is tied to the Off OWLS time within the total time on task. Thus, depicting engagement as a process where various attributes of engagement vary in intensity and are inherent at different phases of the process as shown in the process model of engagement (O'Brien & Toms, 2008). These insights will be useful in designing cyberlearning based learning environments and also for design similar cyberlearning systems.

7.7 Limitations

The results discussed above are found by two in-class applications of the OWLS. So, first, the generalizability of the results should be made with caution. More studies are needed in a variety of contexts to generalize the findings. For example, these results were found out in the context of the OWLS, so if the cyberlearning system changes the result might differ since according to situative perspective of learning, the material context impacts how students learn. Again, if the OWLS-based experiment is not conducted within a classroom environment or if students' population has different background knowledge the results might be different. Students' learning and engagement might also be different if students interacted with the OWLS for a longer time period or they were familiar with the OWLS. However, the intention of this study was not to generalize the result, rather explore how individual students learn and engage with the OWLS for the specific OWLS-based tasks. Second, in this study, it was interesting to find the significant differences in students' learning and engagement due to different factors, such as gender, and background knowledge of water quality. But as discussed earlier, these trends need further investigation as the sample size for each group for a factor was small and not proportional. For that case, the study can be repeated with a bigger and more proportional sample size to evaluate if the study results are consistent. However, effect size was calculated to measure the standardized difference between the groups to address this limitation in the study. Third, the study did not have a control group to compare and conclude results based on a benchmark. The results were able to bring out the various nuances of engagement and learning and explore the relationships that might exist between the learning and engagement variables in the context of the particular groups of students, who accessed the OWLS. Thus, in this study it is difficult to conclude whether OWLS is more effective in engaging students to learn environmental monitoring concepts, which was also not the aim of the study. Finally, for the small sample size the confirmatory factor analysis could not be carried out to examine how well the data collected with the UES items represent the six attributes of engagement in the OWLS context. In other words the validity of the UES in the context of this research could not be investigated. Implementation of the UES was beneficial in demonstrating the psychological state of students' engagement.

7.8 Implications for Research and Practice

This study provided several outcomes related to individualized learning and engagement within a cyberlearning system, in the context of the OWLS utilized by students for completing an environmental monitoring task within a classroom environment. The specific implications to research and practice are discussed below.

7.8.1 Implications for Research

Advanced OWLS in the context of personalized learning. There are several implications for research. First, this study advanced research potential of the OWLS in the context of personalized learning. This version of the OWLS with the user-tracking system can be utilized in any future research agenda related to the in-depth assessment of student learning. For example, based on this study, a NSF research proposal was submitted that aimed to enhance environmental monitoring education in seven disciplines across two institutes and to conduct research related to personalized and group learning utilizing user-tracking data.

Presents computational architecture of a user-tracking system. Second, the study demonstrates engineering education researchers an example of technologies and functionalities that can be incorporated to develop an effective and secure user-tracking system for a cyberlearning platform. The user-tracking system not only detects users across devices and collects their temporal navigational pattern as well as stores their actions and selections within the system into a database. Moreover, 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 at regular intervals of time.

Demonstrates an analytical framework. Third, this study presents an analytical approach that can be utilized by researchers for holistic investigation of individual learning and engagement within computer-mediated interactive systems including cyberlearning systems. This method utilized both behavioral measures of student engagement and self-report measures that complement and help in the understanding of the behavioral measures, for interpreting students' engagement with a cyberlearning system. For evaluating students learning, both direct and indirect measure was incorporated. Additionally, students' perception towards the learning value of each of the components of the cyberlearning system was assessed. All these data was effective in bringing out the relationship of the parameters in the context of the users and their task completion experience with a cyberlearning system and provides sufficient evidence to conform to the fact that engagement and learning is context and user dependent.

Presents insight into students' learning and engagement. Fourth, the study presents several insights into students' learning and engagement within a cyberlearning system, such as the OWLS that can be utilized to design effective and engaging cyberlearning systems. For example, it is seen that students' resource utilization is related to the task requirements. This prompts that proper utilization of a cyberlearning system can depend on effective design of tasks. Again, aesthetics is seen to be positively and significantly related to students' learning. Thus, aesthetic of a cyberlearning system can be improved to make it more engaging to students. These insights also inform the literature on learning analytics and educational data mining.

Lays the foundation for future research in advancing OWLS to an adaptable system. Finally, this study laid the foundation for future research in making the OWLS capable of providing individualized feedback and thus making it adaptable to personalized learning needs. In this study, data mining techniques were applied to students' temporal navigation patterns to find frequent action patterns and to identify differentially frequent patterns between two groups of students. These data will be further analyzed to find productive and counter-productive actions in relation to students' learning. Detection of such actions can help in identifying the individualized feedback that needs to be given to the students for improving their learning.

7.8.2 Implications for Practice

This research has various implications for faculty members and more specifically for faculty members teaching courses related to environmental monitoring.

Provides recommendation for instructional design. First, the study provides recommendations for instructional design using cyberlearning systems. The results showed that students' learning outcome was significantly better when the OWLS-based task had the instruction sequence presented in the ascending order of bloom's taxonomy, compared to a different sequence of instructions, though all students attempted the same set of questions. This result needs to be verified with bigger sample size, nevertheless, it indicates that attention needs to be given to the way instructions are presented when developing learning activities with cyberlearning systems.

Presents insights for integrating cyberlearning systems into the curriculum. The study provides several insights to the process of integration of cyberlearning systems into a classroom environment for leveraging technology-enhanced education. Instructors interested in using systems like OWLS will be able to get ideas from this study on developing learning activity with a cyberleraning system and creating rubrics for evaluation. Further, the study will help them to understand how each student might learn and engage within a cyberlearning system that will allow educators to: i) evaluate and predict students' performances, ii) understand the efficacy of the learning materials, and iii) validate/evaluate the teaching strategies.

Demonstrates the utilization of real-life case-studies for student learning. This study demonstrates to instructors how case-studies can be utilized for exposing students to real-world problems and engaging them to solve problems appropriate to their levels, which can improve student learning. Consequently, this study promotes the effective design of learning environments and proper selection of pedagogical approaches to guide interactions in classroom settings that can be extended to online and distance learning settings.

7.8 Future Work

This study can have multiple future directions. Here are few examples. First, the study can be conducted in variety of contexts. For example, the study can be carried out with a bigger sample size to generalize the results. This study can be carried out in presence of a control group to evaluate effectiveness of OWLS in engaging students. Next, it can be replicated with students from various academic levels or disciplines to compare and contrast the ways students learn and engage with the OWLS. The study can be carried out with national and international students, to whom the OWLS represent a local and a remote watershed, respectively. By utilizing the OWLS in different settings, the learning and engagement of the students can be investigated. Second, in this study, students had to complete their task within the in-class time. It will be interesting to find out how students' engagement and learning with the OWLS differ if students are to complete the OWLS-based task without a time limit. Although, cautionary steps need to be taken to address the confounding variables that might occur in this type of situation. Third, user engagement in this study has been measured using self-reports and behavioral indicators. Another way to measure engagement is to use physiological measurements. These can be measured remotely using camera and image processing tools that captures facial expressions, track eye movements and body postures. Direct physiological measurements include application of sensors on students' bodies to capture their heart rate, brain activity and electro-dermal data. These can be used to further extend the understanding about students' engagement with the OWLS. Fourth, further analysis can be done with the already collected user tracking data to identify productive and counter-productive student actions in completing the task. This will help in providing direct feedback to individual students and thus advancing personalized learning. Finally, extending on this work, dashboards can be built within the OWLS to help students visualize and track their actions for improving metacognition and learning.

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Appendix A: Pilot Study Instruments

A.1 OWLS-based Post- Survey

Dear Students,

Today you just completed an OWLS-based assignment called the "Webb-Branch-Watershed-based Environmental Monitoring Task" utilizing the Online Watershed Learning System (OWLS: http://owls.lewas.ictas.vt.edu/login), which is an open-ended guided cyberlearning environment using data from the Learning Enhanced Watershed Assessment System (LEWAS). The OWLS had a login system and a user tracking system that tracked your actions within the OWLS. Your data will be stored securely in the LEWAS database and these data will not affect your grades on the OWLS-based assignment.

This survey is about the OWLS-based assignment. Although the survey is voluntary and confidential, we would very much appreciate your participation. Consent is implied with the submission of the survey. The consent for the survey includes consenting to allowing the analysis of your OWL-based assignment and your actions recorded by the user tracking system within the OWLS, by the researchers. The decision to participate or not to participate in the survey will not affect your grade on the OWLS-based assignment. The survey includes 14 questions and it will take a maximum of 10 minutes to complete. Kindly note if you are a minor, you are requested not to participate in this survey.

Note: The research is conducted by Debarati Basu and Dr. Vinod K. Lohani for the purpose of evaluating the OWLS with its user tracking system, to test out the survey and to test the OWLS-based assignment. The results will be used confidentially for conference and journal publications, and dissertation.

If you have any questions you can contact the researchers: Debarati Basu (debarati@vt.edu, 540-250-0681) and Dr. Vinod K. Lohani (blohani@vt.edu, 540-231-0019).

Should you have any questions or concerns about the study's conduct or your rights as a research subject, you may contact the VT IRB Chair, Dr. David M. Moore at moored@vt.edu or (540) 231-4991.

Best Regards,

Research Team

Q1 Which of the following sessions do you attend for the course ENSC 4414?

o Session I on Monday

o Session II on Friday

Q2 Have you completed or are you currently taking the course Water Quality (ENSC/CSES 4314)?

o Yes

o No

Q3 How would you rate your proficiency in water quality concepts?

o None

o Basic

o Intermediate

o Advanced

o Expert

Q4 How did you access the OWLS?

o Link provided in the OWLS-based assignment

o Using search engine

o Other ____

Q5 Have you ever accessed the OWLS before the assignment was given in this class? If so, when?

____

Q6 The OWLS helped me learn about the Webb Branch Watershed

o Strongly agree

o Agree

o Somewhat agree

o Somewhat disagree

o Disagree

- Strongly disagree

Q7 The OWLS helped me learn the importance/purpose of continuous environmental monitoring

- Strongly Disagree
- Disagree
- Somewhat agree
- Somewhat disagree
- Agree
- Strongly agree

Q8 The OWLS helped me know how to analyze environmental monitoring data

- Strongly agree
- Agree
- Somewhat agree
- Somewhat disagree
- Disagree
- Strongly disagree

Q9 The OWLS helped me relate my theoretical knowledge to real-world water quality events happening in my local Webb Branch watershed.

- Strongly agree
- Agree
- Somewhat agree
- Somewhat disagree
- Disagree
- Strongly disagree

Q10 The OWLS helped me to identify real-world events

o Strongly agree

o Agree

o Somewhat agree

o Somewhat disagree

o Disagree

o Strongly disagree

Q11 In the OWLS-based assignment you explored various components of the OWLS.

What was the learning value of the following components of the OWLS :

	Not valuable	Somewhat valuable	Valuable	Extremely valuable
Interactive graphs	❍	❍	❍	❍
Overhead view/map	❍	❍	❍	❍
Case studies	❍	❍	❍	❍
Background information	❍	❍	❍	❍
Live LEWAS data	❍	❍	❍	❍
Data download	❍	❍	❍	❍
How-to-Use Guide	❍	❍	❍	❍
Live Camera	❍	❍	❍	❍
Weather Radar	❍	❍	❍	❍
Storm View	❍	❍	❍	❍
Glossary	❍	❍	❍	❍
Others	❍	❍	❍	❍

Q12 Comment on your overall experience with the OWLS-based assignment

____

____

Q13 Please explain the challenges you faced while completing the OWLS-based assignment, if any.

____

____

Q14 Please indicate your gender

o Male

o Female

Q15 What is your VT email id?

Topic	*Subtopics*	*1 point*	*2 points*	*3 points*

A.2 Rubric for OWLS-based Assignment

Describe the Webb branch Watershed (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	only qualitative/quantitative description without too much analysis	Both quantitative and qualitative description with good analysis	Both 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	Two benefits	More than two benefits
	Case study example	Case study mentioned	Case study mentioned and discussed qualitatively /quantitatively well	Case study mentioned and discussed qualitatively and quantitatively with evidences of pictures/graphs
Select and analyze an Environmental Event shown on the OWLS (8 points)	Start, end time of the event	Presented (Answer: around 1.30 -4.30am on April 18)		
	Highest specific conductance value during the event	Presented (429000microS/cm at 2.39am)		
	Average specific conductance values during the event	Values presented (around 12100microS/cm)		
	Average specific conductance values after the event	Values presented (around 1770.9microS/cm)	Values presented with graph and imagery	
	Reflect on how it might affect the aquatic species in the Webb Branch watershed	Some reflection	In-depth reflection	

Appendix B: Final Implementation Instruments

B.1 OWLS-based Pre- Survey

Q1 Dear Students,

This pre-survey is a part of a dissertation work in the department of Engineering Education. Our goal is to assess students' learning and engagement within a cyberlearning system for environmental monitoring education. You will utilize a cyberlearning system in a later part of the semester to complete the "Water Quality Project" in the class. The cyberlearning system has a login system and a user tracking system that will track your actions within the cyberlearning system. Your data will be stored securely in the database of the researcher's lab and these data will not affect your grades on the water quality project.

The purpose of this pre-survey is to collect some background information about you, which will be helpful for our data analysis. Although the survey is voluntary and confidential, we would very much appreciate your participation. Consent is implied with the submission of the survey. The consent for the survey includes consenting to allowing the analysis of your water quality project response and your actions recorded by the user tracking system within the cyberlearning system, by the researchers. The decision to participate or not to participate in the survey will not affect your grade on the water quality project. The survey includes 16 questions and it will take a maximum of 10 minutes to complete.

Kindly note if you are a minor (below 18 years of age), you are requested not to participate in this survey.

Note: The research is conducted by Debarati Basu and Dr. Vinod K. Lohani for the purpose of evaluating a cyberlearning system with its user tracking system. The results will be used confidentially for conference and journal publications, and dissertation.

If you have any questions you can contact the researchers: Debarati Basu (debarati@vt.edu, 540-250-0681) and Dr. Vinod K. Lohani (vlohani@vt.edu, 540-231-0019).

Should you have any questions or concerns about the study's conduct or your rights as a research subject, you may contact the VT IRB Chair, Dr. David M. Moore at moored@vt.edu or (540) 231-4991.

Best Regards,

Research Team

Q2 How many water resource/quality courses have you taken, excluding this course?

- None
- One to Two Course/s
- Three to Four Courses
- Five to Six Courses
- Seven to Eight Courses

Q3 Please name the water resource/quality course/s you have taken, excluding this course.

____

____

Q4 How would you rate your proficiency in water quality concepts?

- ❍ None
- ❍ Basic
- ❍ Intermediate
- ❍ Advanced
- ❍ Expert

Page Break

Q5 Identify the water quality parameters that have distinct diurnal (daily) variation:

- ❍ Dissolved oxygen and turbidity
- ❍ Dissolved oxygen and water temperature
- ❍ Water temperature and specific conductivity
- ❍ Turbidity and specific conductivity

Q6 Solubility of oxygen is higher at 0 deg C compared to at 15 deg C:

- ❍ True
- ❍ False

Q7 During a summer thunderstorm the water temperature in the stream will increase:

- ❍ True
- ❍ False

Q8 The land use of the local Web Branch watershed is best described as:

- Forest land
- Mixed land use
- Agriculture land
- Urban land

Q9 Which of the following conditions will induce high peak discharge rate of relatively short duration, i.e. the stream responds to events quickly and returns to base flow conditions quickly?

- Small drainage area and agricultural land
- Agricultural Land and large drainage area
- Small drainage area and highly impervious land
- Large drainage area and highly impervious land

Q10 Specific Conductivity will usually ---------?---------- in the local Web branch watershed during a winter storm event.

- increase
- decrease

Q11 Select among the following that are directly related to the continuous modeling of water quality parameters:1. Expensive 2. Requires frequent calibration of sensors3. Requires interdisciplinary expertise4. Can help in identifying unusual water quality events

- Only 1
- Only 1 and 2
- Only 1, 2 and 4
- 1, 2, 3 and 4

Q12 Data errors from the continuous water quality monitoring station can always be attributed to environmental (natural) factors:

- True
- False

Q13 What can be the reason for high turbidity in a stream, if there is no storm event?

- Overcast day
- Water main break
- Gradual widening of stream
- High water temperature

Page Break

Q14 What gender were you assigned at birth on your original birth certificate?

- Male
- Female

Q15 Please indicate your ethnicity

- White/Caucasians
- Black/African American
- American Indian/ Alaska Native
- Asian
- Native Hawaiian/ Pacific Islander
- Others

Q16 What is your VT email id?

B.2 Slides Used During Training Session

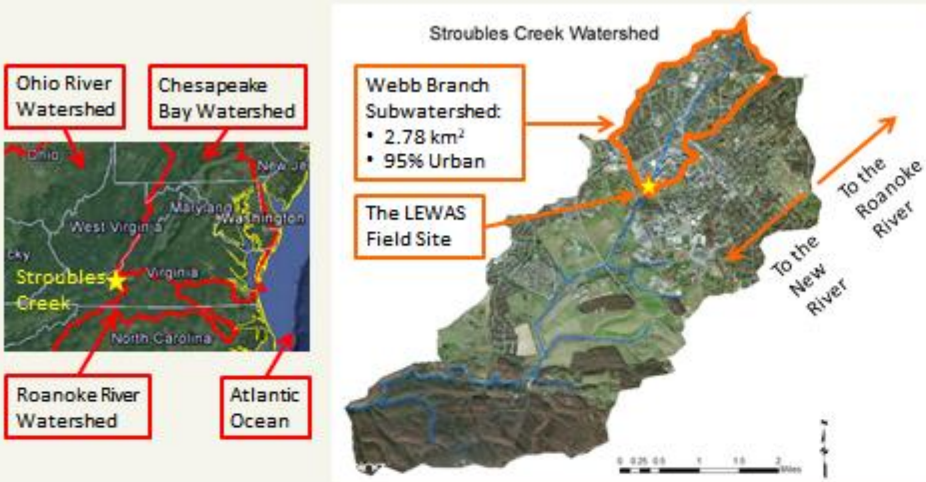
Agenda

- What is a watershed?
- Why we do continuous environmental mentoring?
- Different components of LEWAS
- Demonstration and exploration of a cyberlearning system
- Practice problems

What is a watershed?

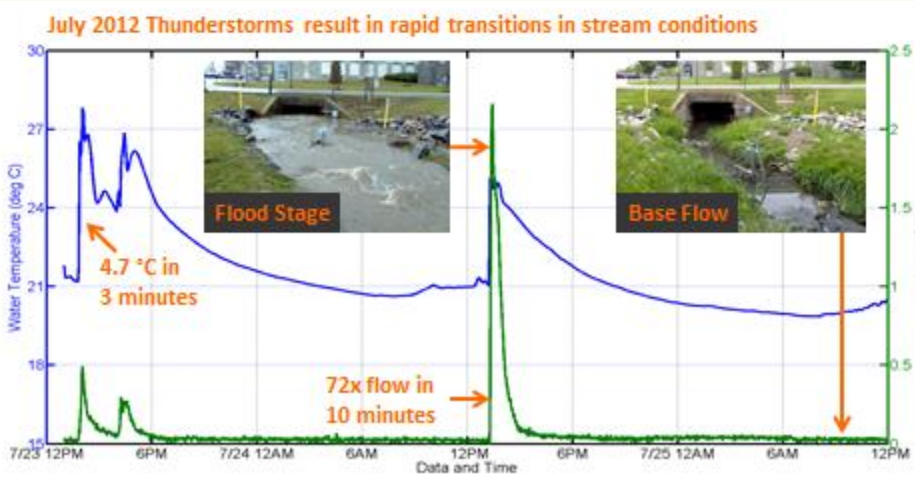
An area or ridge of land that separates waters flowing to different rivers, basins, or seas.

Location of the LEWAS Field Site

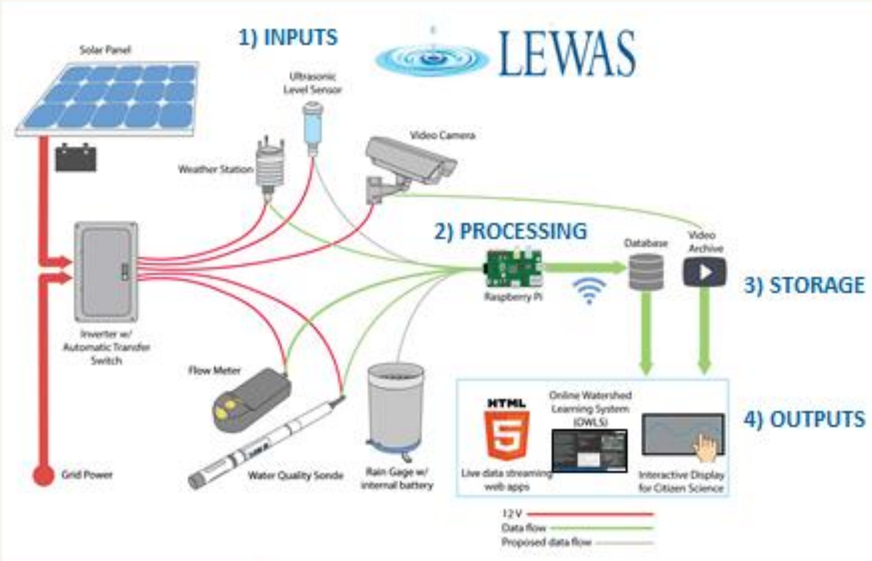


High-Resolution Data

The LEWAS produces real-time, high-resolution data that provides opportunities for innovative research and education.



LEWAS Data Flow



LEWAS LAB
LEARNING ENHANCED WATERSHED ASSESSMENT SYSTEM

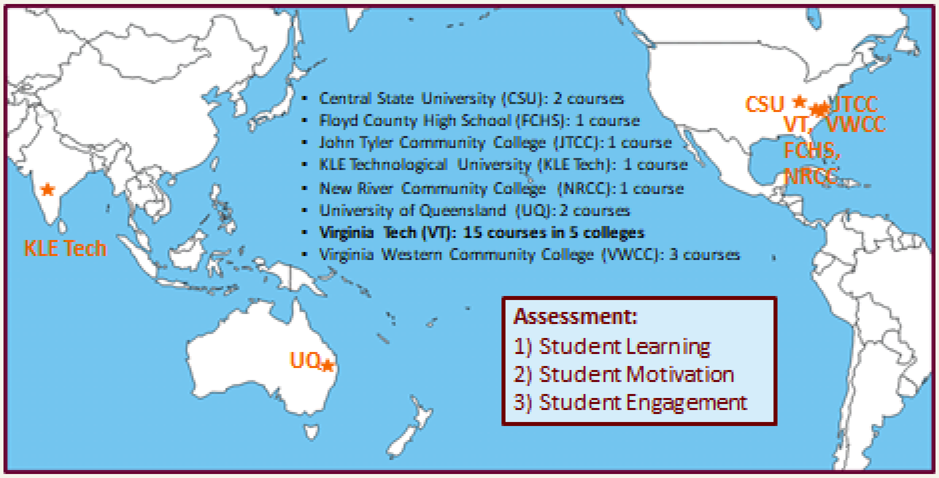
VirginiaTech *Invent the Future* 7

Students using the OWLS

LEWAS LAB
LEARNING ENHANCED WATERSHED ASSESSMENT SYSTEM

VirginiaTech *Invent the Future* 8

Settings: LEWAS/OWLS Use in Education



Adapted from http://d-maps.com/carte.php?num_car=3502&lang=en

LEWAS LAB
LEARNING ENHANCED WATERSHED ASSESSMENT SYSTEM

VirginiaTech Invent the Future 9

To know more about us

LEWAS Homepage: http://www.lewas.centers.vt.edu/

OWLS Homepage: http://owls.lewas.ictas.vt.edu

LEWAS Intro Video:
https://www.youtube.com/watch?v=rS6cWdCgK3A

LEWAS Twitter Feed: https://twitter.com/LEWASLab

LEWAS LAB
LEARNING ENHANCED WATERSHED ASSESSMENT SYSTEM

VirginiaTech Invent the Future 10

B.3 OWLS-based Training Sheet

Instruction sheet

The Learning Enhanced Watershed Assessment System (LEWAS) is a unique real-time environmental monitoring system that has been developed at Virginia Tech in Blacksburg to enhance environmental 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 at every 1-3 min continuously for 24 hours. LEWAS has an open-ended, guided cyberlearning system called the **Online Watershed Learning System** (**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. OWLS has been designed so that a user can explore its various components to learn about the LEWAS field site, the Webb Branch watershed, environmental parameters, changes of the environmental parameters over time, and to understand different environmental events. A user has the ability to download data from the OWLS for calculations, and to compare, contrast and analyze the environmental data. You will use OWLS in your next class to complete your water quality project!

Please follow these instructions:

1. Use the above link to access the OWLS
2. Click the "**Signup**" word on the Login page to create your account. Use your **VT email** id (example@vt.edu) to sign up.
3. Please **keep a note of your password**
4. Use only **one browser** to access the OWLS
5. **Do not use any other browser** for any other task now
6. Explore all the OWLS components
7. Practice data analysis with the OWLS
8. **Logout** (link on the home page) out from the OWLS after completing this training session

Practice data analysis with the OWLS:

1. Explore the pH values from the 30th Aug to 26th of September, 2017.

Find the following:

Maximum pH value-

Minimum pH value-

Average pH value-

2. Explore the dissolved oxygen (DO) and oxidation reduction potential (ORP) values from the 1st to 3rd of September, 2017. Describe the relationship between DO and ORP.

B.4 OWLS-based Sign In Sheet

First name:	
Middle name:	
Last name:	
Email Id used for OWLS login:	
Project set:	

B.5 OWLS-based Water Quality Project (OWLS-based Task)

OWLS-based Water Quality Project (Set A)

The Learning Enhanced Watershed Assessment System (LEWAS) is a unique real-time environmental monitoring system that has been developed at Virginia Tech in Blacksburg to enhance environmental 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 at every 1-3 min continuously for 24 hours. LEWAS has an open-ended, guided cyberlearning system called the **Online Watershed Learning System** (**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. OWLS has been designed so that a user can explore its various components to learn about the LEWAS field site, the Webb Branch watershed, environmental parameters, changes of the environmental parameters over time, and to understand different environmental events. A user has the ability to download data for calculations, and to compare, contrast and analyze the environmental data.

In this OWLS-based water quality project, you will remotely conduct continuous environmental monitoring of the Webb Branch watershed using the OWLS. Please follow the below instructions:

1. Login to the OWLS with your **VT email** address and password
2. Use only **one browser** to access the OWLS
3. **Do not use any other browser** for any other task
4. **Do not engage in any other task** while completing this project on your own
5. **Logout** (link on the home page) from the OWLS after completion of the project
6. **Submit** the project report/response document to canvas under homework
7. **Complete the post-survey** (voluntary) after completing the project [link provided in the canvas announcement]

Please explain with supporting evidences of data, graph and/or imagery from the OWLS, wherever appropriate. Explain your answers in **a word document** to the following 3 questions:

1. **Analyze dissolved oxygen (DO) and water temperature data from the LEWAS field site (10 points):**

a. For each of the two time periods, 1st to 30th January 2016 and 10th to 28th August 2016 data:

- Download data and save it as Excel file (.xls)
- Provide the range for water temperature
- Calculate the average water temperature
- Provide the range for DO
- Calculate the average DO
- Describe the relationship between DO and water temperature

[Hints: MS Excel built in functions can be used for data analysis.]

b. Compare the above (1a) results for the two time periods in January and August.

2. **Describe the Webb Branch Watershed (5 points)**
Explore the OWLS to qualitatively and quantitatively describe the Webb Branch watershed. Describe the variations in Specific conductance, pH and water temperature values in for the current time period (27th to 28th Sept., 2017).
3. **What are the benefits of continuous environmental monitoring as is being done at the LEWAS site? (5 points)**
For this purpose, you are expected to explore the case studies that are available from the OWLS. You must include example of at least one case study in describing the benefits.

OWLS-based Water Quality Project (Set B)

The Learning Enhanced Watershed Assessment System (LEWAS) is a unique real-time environmental monitoring system that has been developed at Virginia Tech in Blacksburg to enhance environmental 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 at every 1-3 min continuously for 24 hours. LEWAS has an open-ended, guided cyberlearning system called the **Online Watershed Learning System** (**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. OWLS has been designed so that a user can explore its various components to learn about the LEWAS field site, the Webb Branch watershed, environmental parameters, changes of the environmental parameters over time, and to understand different environmental events. A user has the ability to download data for calculations, and to compare, contrast and analyze the environmental data.

In this OWLS-based water quality project, you will remotely conduct continuous environmental monitoring of the Webb Branch watershed using the OWLS. Please follow the below instructions:

1. Login to the OWLS with your **VT email** address and password
2. Use only **one browser** to access the OWLS
3. **Do not use any other browser** for any other task
4. **Do not engage in any other task** while completing this project on your own
5. **Logout** (link on the home page) from the OWLS after completion of the project
6. **Submit** the project report/response document to canvas under homework
7. **Complete the post-survey** (voluntary) after completing the project [link provided in the canvas announcement].

<u>Please explain with supporting evidences of data, graph and/or imagery from the OWLS, wherever appropriate. Explain your answers in **a word document** to the following 3 questions:</u>

4. **Describe the Webb Branch Watershed (5 points)**
   Explore the OWLS to qualitatively and quantitatively describe the Webb Branch watershed. Describe the variations in Specific conductivity, pH and water temperature values for the current time period (27^{th} to 28^{th} Sept., 2017).
5. **What are the benefits of continuous environmental monitoring as is being done at the LEWAS site? (5 points)**
   For this purpose, you are expected to explore the case studies that are available from the OWLS. You must include example of at least one case study in describing the benefits.
6. **Analyze dissolved oxygen (DO) and water temperature data from the LEWAS field site (10 points):**
   c. For each of the two time periods, 1^{st} to 30^{th} January 2016 and 10^{th} to 28^{th} August 2016 data:
      - Download data and save it as Excel file (.xls)
      - Provide the range for water temperature
      - Calculate the average water temperature
      - Provide the range for DO
      - Calculate the average DO
      - Describe the relationship between DO and water temperature

[Hints: MS Excel built in functions can be used for data analysis.]

d. Compare the above (1a) results for the two time periods in January and August.

B.6 Rubric for OWLS-based Task

Topic	*Subtopics*	*1 point*	*2 points*	*3 points*
Describe the Webb branch Watershed (5 points)	Watershed Description	Mentioned one characteristics	Mentioned 2-3 characteristics with qual./quant description	Thorough description with more than 3 qual. and quant characteristics
	Description of the variations in water quality parameters for the current day	Only qualitative description of the water quality parameters; not too much analysis	Both quantitative and qualitative description of of the water quality parameters; good analysis; Deduct 0.5 if numbers are present without description	
Benefits of continuous environmental monitoring as is being done at the LEWAS site (5 points)	Benefit discussion	One benefit	Two benefits	More than two benefits or two benefits with nice description of 2 case studies
	Case study example	One case study mentioned	One case study mentioned and described it	
Analyze Dissolved Oxygen (DO) and Water Temperature (WT) data from the LEWAS field site (10 points)	DO			Max DO, Min DO, Avg DO for two time periods (0.5*6)
	Water temp.			Max WT, Min WT, Avg WT for two time periods (0.5*6)
	Relationship between DO and water temp.	For two time periods written separately or written once		
	Result comparison	Only one parameter compared	Diff between DO and water temp. values in Jan and Aug detected	Diff between DO and water temp. values in Jan and Aug detected and similarity between DO and water temp in both months identified

B.7 OWLS-based Post-Survey

Water Quality Project Post-Survey

Q1 Dear Students,

Today you just completed an OWLS-based water quality project utilizing the Online Watershed Learning System (OWLS available at http://owls.lewas.ictas.vt.edu/login), which is an open-ended and guided cyberlearning environment using data from the Learning Enhanced Watershed Assessment System (LEWAS). The OWLS has a login system and a user tracking system that tracks your actions within the OWLS. Your data will be stored securely in the LEWAS database and these data will not affect your grades on the water quality project.

This survey is about the experience you had after completing the OWLS-based water quality project. Although the survey is voluntary and confidential, we would very much appreciate your participation. Consent is implied with the submission of the survey. The consent for the survey includes consenting to allow researchers to analyze your water quality project response and your actions recorded by the user tracking system of the OWLS during the week of September 25, 2017 and also to collect your course grade from CEE 3104. The decision to participate or not to participate in the survey will not affect your grade on the OWLS-based water quality project. The survey includes 57 questions and it will take a maximum of 20 minutes to complete.

Kindly note if you are a minor (below 18 years of age), you are requested not to participate in this survey.

Note: The research is conducted by Debarati Basu and Dr. Vinod K. Lohani for the purpose of evaluating the OWLS with its user tracking system, to test out the survey and to test the OWLS-based assignment. The results will be used confidentially for conference and journal publications, and dissertation.

If you have any questions about the research, you can contact the researchers: Debarati Basu (debarati@vt.edu, 540-250-0681) and Dr. Vinod K. Lohani (vlohani@vt.edu, 540-231-0019).

Should you have any questions or concerns about the study's conduct or your rights as a research subject, you may contact the VT IRB Chair, Dr. David M. Moore at moored@vt.edu or (540) 231-4991.

Best Regards,

Research Team

Q2 Have you accessed the Online Watershed Learning System (OWLS) in any of your earlier course/s other than CEE 3104?

o Yes

o No

Q3 If you have answered yes in the previous question, please write the name of the course/s where you have accessed the OWLS. If you have answered no, then write "N.A." here.

____

____

Q4 Have you ever accessed the OWLS before this week (Week of Sept. 25) in CEE 3104? If so, when?

____

Q5 How did you access the OWLS for the water quality project?

o Link provided in the OWLS-based water quality project

o Using search engine

o Other ____

Q6 How would you rate your proficiency in water resource/quality concepts?

o None

o Basic

o Intermediate

o Advanced

o Expert

Q7 The OWLS helped me learn about the Webb Branch Watershed:

o Strongly agree

o Agree

o Somewhat agree

o Somewhat disagree

o Disagree

o Strongly disagree

Q8 The OWLS helped me learn the importance/purpose of continuous environmental monitoring:

o Strongly Disagree

o Disagree

o Somewhat agree

o Somewhat disagree

o Agree

o Strongly agree

Q9 The OWLS helped me know how to analyze environmental monitoring data:

o Strongly agree

o Agree

o Somewhat agree

o Somewhat disagree

o Disagree

o Strongly disagree

Q10 The OWLS helped me relate my theoretical knowledge to real-world water quality events happening in my local Webb Branch watershed:

o Strongly agree

o Agree

o Somewhat agree

o Somewhat disagree

o Disagree

o Strongly disagree

Q11 The OWLS helped me to identify water quality changes:

- o Strongly agree
- o Agree
- o Somewhat agree
- o Somewhat disagree
- o Disagree
- o Strongly disagree

Q12 During this in-class water quality project, you explored various components of the OWLS.

What was the learning value of the following components of the OWLS :

	Not valuable	Somewhat valuable	Valuable	Extremely valuable
Overhead view/map	❍	❍	❍	❍
Case studies	❍	❍	❍	❍
LEWAS Intro	❍	❍	❍	❍
Watershed Summary	❍	❍	❍	❍
Live LEWAS data	❍	❍	❍	❍
Data download	❍	❍	❍	❍
Site Map	❍	❍	❍	❍
Key components	❍	❍	❍	❍
Photo Index	❍	❍	❍	❍
Home Page	❍	❍	❍	❍
Live Camera	❍	❍	❍	❍
Weather/Doppler Radar	❍	❍	❍	❍
Storm View	❍	❍	❍	❍
Glossary	❍	❍	❍	❍

Others	❍	❍	❍	❍

Q13 Identify the water quality parameters that have distinct diurnal (daily) variation:

- o Dissolved oxygen and turbidity
- o Dissolved oxygen and water temperature
- o Water temperature and specific conductivity
- o Turbidity and Specific Conductivity

Q14 Solubility of oxygen is higher at 0 deg C compared to at 15 deg C:

- o True
- o False

Q15 During a summer thunderstorm the water temperature in the stream will increase:

- o True
- o False

Q16 The land use of the Webb Branch watershed is best described as:

- o Forest land
- o Mixed land use
- o Agricultural land
- o Urban land

Q17 Which of the following conditions will induce high peak discharge rate of relatively short duration, i.e. the stream responds to events quickly and returns to base flow conditions quickly?

- o Small drainage area and agricultural land
- o Agricultural Land and large drainage area
- o Small drainage area and highly impervious land
- o Large drainage area and highly impervious land

Q18 Specific Conductivity will usually ---------?---------- in the local Webb Branch watershed during a winter storm event.

o increase

o decrease

Q19 Select among the following that are directly related to the continuous modeling of water quality parameters at a site like the LEWAS:1. Expensive 2. Requires frequent calibration of sensors3. Requires interdisciplinary expertise4. Can help in identifying unusual water quality events

o Only 1

o Only 1 and 2

o Only 1, 2 and 3

o 1, 2, 3 and 4

Q20 Data errors from the continuous water quality monitoring station can always be attributed to environmental (natural) factors:

o True

o False

Q21 What can be the reason for high turbidity in a stream, if there is no storm event?

o Overcast day

o Water main break

o Gradual widening of stream

o High water temperature

Q22 These questions will be related to how you were engaged with the OWLS.

Q23 I "lost myself" in this OWLS-based experience

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q24 I was so involved in my OWLS-based project that I lost track of time

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q25 I blocked out things around me when I was completing the OWLS-based project

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q26 When I was completing the OWLS-based project, I lost track of the world around me

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q27 The time I spent completing OWLS-based project just slipped away

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q28 I was absorbed in my OWLS-based project

- o Strongly agree

- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Q29 During this OWLS-based project experience I let myself go

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Q30 I was really drawn into my OWLS-based project

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Q31 I felt involved in this OWLS-based project

- Strongly agree
- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Q32 This OWLS-based project was fun

- Strongly agree
- Agree
- Neither agree nor disagree

o Disagree

o Strongly disagree

Q33 I continued to explore OWLS website out of curiosity

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q34 The content of the OWLS website incited my curiosity

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q35 I felt interested in my OWLS-based project

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q36 Completing the project on the OWLS was worthwhile

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q37 I consider my OWLS-based experience a success

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q38 This OWLS -based experience did not work out the way I had planned

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q39 My OWLS-based experience was rewarding

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q40 I would recommend the OWLS to my friends and family

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q41 This OWLS website is attractive

- o Strongly agree

- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q42 This OWLS website was aesthetically appealing

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q43 I liked the graphics and images used on this OWLS website

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q44 This OWLS website appealed to my visual senses

- o Strongly agree
- o Agree
- o Neither agree nor disagree
- o Disagree
- o Strongly disagree

Q45 The screen layout of this OWLS website was visually pleasing

- o Strongly agree
- o Agree
- o Neither agree nor disagree

o Disagree

o Strongly disagree

Q46 I felt frustrated while visiting this OWLS website

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q47 I found this OWLS website confusing to use

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q48 I felt annoyed while visiting this OWLS website

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q49 I felt discouraged while completing the project on this OWLS

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q50 Using this OWLS website was mentally taxing

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q51 This OWLS-based experience was demanding

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q52 I felt in control of my OWLS-based experience

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q53 I could not do some of the things I needed to do on this OWLS website

o Strongly agree

o Agree

o Neither agree nor disagree

o Disagree

o Strongly disagree

Q54 I was so involved in my OWLS-based task that I lost track of time

o Strongly agree

- Agree
- Neither agree nor disagree
- Disagree
- Strongly disagree

Q55 What did you learn by completing the OWLS-based water quality project?

____

____

Q56 Comment on your overall experience with the OWLS-based water quality project

____

____

Q57 Please explain the challenges you faced while completing the OWLS-based water quality project, if any.

____

____

Q58 What is your GPA?

____

Q59 What is your VT email id or your VT PID?

____

B.8 IRB Approval Letters

For Pilot Study:

VirginiaTech

Office of Research Compliance
Institutional Review Board
North End Center, Suite 4120, Virginia Tech
300 Turner Street NW
Blacksburg, Virginia 24061
540/231-4606 Fax 540/231-0959
email irb@vt.edu
website http://www.irb.vt.edu

MEMORANDUM

DATE:	April 27, 2017
TO:	Vinod Lohani, Debarati Basu
FROM:	Virginia Tech Institutional Review Board (FWA00000572, expires January 29, 2021)
PROTOCOL TITLE:	Understanding students' learning using a Cyberlearning system
IRB NUMBER:	17-481

Effective April 25, 2017, the Virginia Tech Institution Review Board (IRB) Chair, David M Moore, approved the New Application request for the above-mentioned research protocol.

This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.

Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

http://www.irb.vt.edu/pages/responsibilities.htm

(Please review responsibilities before the commencement of your research.)

PROTOCOL INFORMATION:

Approved As:	Exempt, under 45 CFR 46.110 category(ies) 2,4
Protocol Approval Date:	April 25, 2017
Protocol Expiration Date:	N/A
Continuing Review Due Date*:	N/A

*Date a Continuing Review application is due to the IRB office if human subject activities covered under this protocol, including data analysis, are to continue beyond the Protocol Expiration Date.

FEDERALLY FUNDED RESEARCH REQUIREMENTS:

Per federal regulations, 45 CFR 46.103(f), the IRB is required to compare all federally funded grant proposals/work statements to the IRB protocol(s) which cover the human research activities included in the proposal / work statement before funds are released. Note that this requirement does not apply to Exempt and Interim IRB protocols, or grants for which VT is not the primary awardee.

The table on the following page indicates whether grant proposals are related to this IRB protocol, and which of the listed proposals, if any, have been compared to this IRB protocol, if required.

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Date*	OSP Number	Sponsor	Grant Comparison Conducted?

* Date this proposal number was compared, assessed as not requiring comparison, or comparison information was revised.

If this IRB protocol is to cover any other grant proposals, please contact the IRB office (irbadmin@vt.edu) immediately.

For Final Study:

VirginiaTech

Office of Research Compliance
Institutional Review Board
North End Center, Suite 4120, Virginia Tech
300 Turner Street NW
Blacksburg, Virginia 24061
540/231-4606 Fax 540/231-0959
email irb@vt.edu
website http://www.irb.vt.edu

MEMORANDUM

DATE:	September 26, 2017
TO:	Vinod K. Lohani, Debarati Basu
FROM:	Virginia Tech Institutional Review Board (FWA00000572, expires January 29, 2021)
PROTOCOL TITLE:	Understanding students' learning using a Cyberlearning system
IRB NUMBER:	17-481

Effective September 26, 2017, the Virginia Tech Institution Review Board (IRB) Chair, David M Moore, approved the Amendment request for the above-mentioned research protocol.

This approval provides permission to begin the human subject activities outlined in the IRB-approved protocol and supporting documents.

Plans to deviate from the approved protocol and/or supporting documents must be submitted to the IRB as an amendment request and approved by the IRB prior to the implementation of any changes, regardless of how minor, except where necessary to eliminate apparent immediate hazards to the subjects. Report within 5 business days to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

http://www.irb.vt.edu/pages/responsibilities.htm

(Please review responsibilities before the commencement of your research.)

PROTOCOL INFORMATION:

Approved As:	Exempt, under 45 CFR 46.110 category(ies) 2,4
Protocol Approval Date:	April 25, 2017
Protocol Expiration Date:	N/A
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FEDERALLY FUNDED RESEARCH REQUIREMENTS:

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Date*	OSP Number	Sponsor	Grant Comparison Conducted?

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If this IRB protocol is to cover any other grant proposals, please contact the IRB office (irbadmin@vt.edu) immediately.

B.9 Effect Size Calculation

The differnt ways to calculate the effect size are shown below (Ellis, 2009):

Cohen's d = M_1- M_2/ SD pooled

Hedges' g = M_1- M_2/ SD*pooled

Where, M_1 and M_2 are the means of two groups, which are compared to find the standardized mean difference between the groups. SD is the standard deviation of the population from which the two groups are sampled. The Cohen's d formula can be used if the samples of the two groups are of same size (Cohen,1988). For Cohen's d the following equation is used to calculate the SD pooled (Cohen, 1988, p44):

$$SD_{pooled} = \sqrt{\frac{(SD_1^2 + SD_2^2)}{2}}$$

However for some of the comparisons in this study, the sample sizes of the two groups were different, for which the standard deviation of each group is weighted by the sample size and thus the Hedges' g formula is chosen. To calculate the SD^*pooled the following equation is used to calculate the SD^*pooled (Hedges, 1981, p.110):

$$SD^*_{pooled} = \sqrt{\frac{(n_1 - 1)SD_1^2 + (n_2 - 1)SD_2^2}{n_1 + n_2 - 2}}$$

Where n_1 and n_2 are the sample size of the two groups and SD_1 and SD_2 are the standard deviations of the two groups.

Using Hedge'g formula an example effect size calculation is shown below comparing the learning scores of Set A and B students:

Set	A	n_2 =30	M_2 =16.78	SD_2 =0.33
	B	n_1=22	M_1 =18.43	SD_1 =0.39

Hedges' g= (18.43-16.78)/ sqrt ((22-1)*0.39^2+(30-1)*0.33^2/30+22-2)

= 1.65/ sqrt (3.194+/50)

= 1.65/sqrt (0.127)

= 4.63

Appendix C: Codes Written for the Advancement of the OWLS

The latest version of the OWLS 4.2 with the user-tracking system is stored in GitHub account of the LEWAS lab: https://github.com/lewas-lab/owls-login

The below screen shot shows the various files written for developing the user-tracking system of the OWLS:

```
▼ owls-login
  ▼ app
    ▼ models
        user.js
        user_req.js
      routes.js
  ▼ config
      database.js
      passport.js
  ▶ private
  ▼ views
      error.ejs
      forgot.ejs
      login.ejs
      reset.ejs
      signup.ejs
    .gitignore
    app.js
    package.json
```

The user-tracking system also includes the user-tracking functionalities that can capture users' interactions within each of the OWLS html webpages. For this, codes were added to all the "*.html" webpages of the OWLS, for example camera.html, and caseStudy_sedimentation.html, and JavaScript functions were added in the owls.js file, which are hidden under the "private" section in the above figure.

For adding the data availability and visualization features, the following files of the OWLS were updated: single_graph.html, rawData.html, data_corrections.html, owls.css and owls.js. Specifically single_graph.html and rawData.html was recoded to simplify the html code, D3-based JavaScript functionalities were added to the owls.js page and owls.css was updated to support the newly coded html pages.