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EFFECTS OF INDIVIDUAL DIFFERENCES AND VISUAL INFORMATION SEEKING ON LEARNING STRATEGIES IN ESSAY WRITING

BY

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The future of learning.

Approval of Thesis

The undersigned certify that they have read the thesis entitled

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Submitted by

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Dedication

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Abstract

When learners seek information on unfamiliar topics, one technique used is exploratory search. Broadly speaking, there are three different searching activities; lookup, learning, and investigating. Exploratory searching focuses on the learning and investigating activities, and primarily relies on navigation, selection, and trial-and-error strategies. Researchers have proposed using visual representations of topics called concept maps to allow learners to better deal with large quantities of information. In this work, we investigate the effects of individual differences and information visualization on exploratory search with respect to self-directed learning. Our findings indicated a positive correlation between perceived prior knowledge and the time spent on task, as well as a positive correlation between time on task and the overall score achieved on the task. However, we were unable to find a correlation between other individual differences, the use of the concept map tool, and the learning outcomes in the assigned exploratory learning tasks.

Keywords: learning, information visualization, motivation, exploratory search, goal setting theory, goal-oriented learning, learning strategies

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Chapter 1. Introduction

1.1. Background

Humanity is living in an information age, defined by a shift from industrialization towards social, economic, and technological focus on knowledge [Castells 2011; Shapiro 2013]. This viewpoint is not isolated or unique; it appears in and has shaped the direction of research studies in philosophy, sociology, psychology, economics, political science, law, computing science, as well as education [Castells 2011; Kellerman 2000; Poole 2014; Tyner 2014]. When considering the study of education, and the study of learning, the rise of self-directed learning combined with the depth and breadth of information available to learners, has led to several developments in learning theory [McLoughlin 2010; Wang 2012]. Studying and understanding self-directed learning has broad implications across not only education, but also technology, particularly the fields of information search and information visualization.

When learners are seeking out information on topics that they are not familiar with, one of the techniques that they use is exploratory search. In broad terms, search activities are considered to consist of three primary activities; lookup, learning, and investigation. Exploratory search is a more focused type of search that excludes pure lookup tasks and includes only learning and investigation-based search activities [Marchionini 2006; White 2006]. Within these search activities learners primarily rely on three strategies: selection, navigation, and trial-and-error [Marchionini 2006; Puustinen 2009]. The consensus, supported by a number of independent studies, is that exploratory search, when supported by web-based information and search systems, can greatly enhance the process of learning by actively engaging the learner in the learning process, increasing information retention, providing contextual information that would otherwise be unavailable, and (perhaps most importantly), giving more or even complete accountability to the learner [Marchionini 2006; Puustinen 2009; Spink 2002; Stadtler 2011; White 2006]. Exploratory search is a well-established but still relatively new concept as it pertains to learning, and it continues to evolve as web-based information and search technologies become ever more refined and powerful [Marchionini 2006; Spink 2002; White 2006].

One of the challenges with exploratory search is that learners may not have sufficient background knowledge to make sense of the information that they are processing. This is known as the sense-making paradox [Butcher 2011]. A second, related challenge is managing, processing, and tracking the information and the links between related items found during the search process. As learners navigate through and analyze search results, the amount of information being consumed results in a rapidly expanding number of connections between terms and concepts [Marchionini 2006; White 2009]. Studies have shown that when learners using technology based learning find themselves in a situation where they do not have necessary background (domain) knowledge, they are able to make highly targeted analysis and strategic decisions as part of a deep metacognitive process, provided they are given some support, such as visual information cues or adaptive contextual information [Butcher, 2011].

To allow learners to better deal with a large quantity of information in a topic that they are not familiar with, researchers have proposed the use of visualization aides in the form of concept maps [Cañas 2005; Carvalho 2001; Daley 1999; Leake 2004; Novak 2006]. Concept maps are a graph-based visual representation of terms and the relationships between these terms. Concept maps allow for the exploration of a topic all the way from its full scope down to the individual concepts (or terms) that the topic is composed of [Carvalho 2001; Leake 2004]. As such, concept maps allow for the integration of existing knowledge [Cañas 2005; Sebrechts 1999], as well as the creation of new knowledge [Leake 2004; Novak 2006]. The use of concept maps in education is well-researched and well-established [Daley 1999; Horton 1993; Markham 1994; Novak 1990; Novak 1991; Novak 2006], making them a potentially useful tool to help provide structure and guidance to learners engaged in exploratory search.

To evaluate the impact of visualization, it is necessary to consider the individual differences between learners [Davis 1989, Elsweiler 2011]. In particular, we must consider individual differences in terms of the impact of motivation, prior knowledge, and the need for cognition [Cacioppo 1982; Elmborg 2006; Weiler 2005]. While motivation is understood to be a fundamental driver of behavior in all humans, the type of motivation, which can include the need for knowledge or cognition, the need for achievement, the need for affiliation, or the need for power, varies individually and impacts information seeking strategies in different ways [Weiler 2005]. The relative degree of prior knowledge has been shown to impact how a learner begins the learning process, which is particularly relevant in non-linear learning situations [Jonassen 2012].

It is worth noting that while motivation has been well studied within the fields of education and learning with respect to learning outcomes [Weiler 2005], the effects of motivation on the process of learning is not well researched with respect to exploratory search [Elsweiler 2011; Marchionini 2006; Weiler 2005; Weinberger 2011; Wilson 2010].

1.2. Significance

Over the past few decades, online web-based learning has seen tremendous growth, which has led to the development of online learning systems, sometimes called learning management systems [Jolliffe 2012; Moore 2013; Ryan 2013]. Learning management systems have become common not just in schooling but also in the workplace [Coates 2005; Dahlstrom 2014; De Smet

2012; Watson 2007]. Given the wide-spread usage of web-based learning management systems, it has been noted that even small improvements to these systems can result in large overall impacts [Hadwin 2007; Mott 2013].

Web-based learning naturally lends itself to self-guided learning methods, and the study of these methods is becoming more important [Hadwin 2007; Saadé 2005]. However, despite the growth of learning management systems, a significant portion of the materials developed using these systems is prescriptive, or directed learning, that provides very rigid guides or paths through the learning materials [Honebein 2015; Mijatovic 2013; Tserendorj 2013]. One potential area of development for learning management systems is the potential switch towards a less linear and more exploratory model. This approach would allow learners to choose a path through the materials that makes the most sense to them. However, although research has indicated that there may be advantages to exploratory learning management systems, there has not been significant effort in this field [De Freitas 2009; DeCaro 2015; Isaías 2015; Tserendorj 2013].

One additional advantage that web-based learning management systems provide over textbooks is that they allow modes of information visualization not possible on static mediums such as textbooks and publications [Burkhard 2005; Fayyad 2002; Klerkx 2004]. Although the benefits, constraints, and problems that data and information visualization brings to fields such as data mining, business intelligence, medicine, statistics, and engineering are well-known, there has been relatively little study into the use of information visualization in online web-based learning [Chen 2010; González 2003; Ke 2015].

One promising area in information visualization is the development of concept maps. Concept maps, or term-net as they are sometimes referred to, have long been used in education

[Cañas 2005; Daley 1999], but they have not yet seen significant application in online learning [Carter-Templeton 2016; Fasihuddin 2016; Wu 2015].

However, to better understand the learning process, and improve electronic learning management systems, it is important to understand the impact of individual differences on the learning process [DeCaro 2015; Gabrielle 2016; Guthrie 2004; Jonassen 2012]. The study of individual differences will help improve understanding of self-directed, web-based learning, and could help improve existing learning management systems, or lead to new learning management systems [Jonassen 2012; Watson 2007].

The research performed in this study represents the application of data visualization (concept maps) to help address the sense-making problems associated with self-directing learning within an online, web-based environment. This approach has potential applications in the fields of education and learning, where concept maps can potentially provide new, powerful methods for learners to visualize learning concepts. There are several open research questions in this area that align with the topics of learning, motivation, individual differences, and data visualization [Elsweiler 2011; Marchionini 2006; Weiler 2005; Weinberger 2011; Wilson 2010].

1.3. Research Plan Summary

In our research, we conducted a descriptive study to evaluate the use of a concept map (or term-net) and search tool to assist learners in creating a short essay on a specific topic. We considered individual differences using questionnaires that captured Achievement Goal Orientation (AGO), Need for Cognition (NFC), and Prior Knowledge Assessment (PKA) scores. Once participants completed their essay, we asked them to complete perceived usefulness questionnaires for the concept map and search tool, as well as complete a self-assessment of the accuracy of their results.

Chapter 2. Literature Review

2.2. Self-Directed and Self-Regulated Learning

Technology has long been seen as a tool that can help improve the education experience, and research studies have confirmed that technology can be an important enabler, improving not just quantitative aspects, but qualitative aspects of learning as well [Allen 2013; Collins 2010; Facer 2011; Selwyn 2011; Tondeur 2012]. In addition, technology can also provide opportunities for students that would not otherwise be able to access learning materials [Bates 2005; Gabrielle 2016, Wang 2012]. Studies have found that the impacts of technology can be so significant that it requires educators to rethink their approaches and methodologies [Allen 2013; Collins 2010]. However, although evidence points towards technology having generally positive impacts on education, studies have found that the amount of change required can sometimes be a barrier for educators [Selwyn 2011] and, at a minimum, it requires proper education, training, and preparation for the educators themselves [Tondeur 2012].

Research into learning methodologies has found evidence that self-directed learning has become one of the most common methods of learning [Harris 2003; Inkelas 2003; Jung 2002; McLoughlin 2010; Wang 2012]. Self-directed learning has long been a component of curriculum-based education [Barrows 1986; Brookfield 1985; Harris 2003], however, it is also increasingly becoming the primary method of delivering education [Harris 2009; Wang 2012]. This is particularly true for online, web-based learning, where it is possible for the entire learning experience from start to finish to be delivered using a self-directed learning approach [Harris 2009; Lee 2014; Wang 2012].

Numerous models have been proposed for self-regulated learning, however, there are several common attributes to these models. Self-regulated learning is typically an active, rather than a passive or reactive process, with learners participating constructively in the learning process [Pintrich 2000; Rovers 2018]. The self-regulation process is also frequently cyclical, with individuals altering their behavior over time in response to their performance. Zimmerman describes a behavioral self-regulated learning process, where an individual alters their behavior in response to their performance, as well as environmental self-regulation, where an individual modifies some aspect of their environment in response to their performance [Zimmerman 2000].

One model for representing self-regulated learning is COPES, which stands for Conditions, Operations, Products, Evaluations, and Standards [Winne 1997]. Within the COPES model, *conditions* are the states and circumstances identified by learners as being relevant to their task. The *operations* are the tasks and activities that a learner is able to carry out. The *products* are the end outputs of the operations that learners perform. Finally, *evaluation* refers to how learners evaluate the quality of the work they have completed against the *standards* they set, create, or identify. The COPES model defines conditions, operations, and standards as being more malleable components of the self-regulated learning process, while it defines products and evaluation as being less malleable. The COPES model is relevant to our study, as it holds central the idea that self-regulated learning consists of sequences of events and patterns, which are are defined to be discrete tasks or activities with a defined start, action or output, and an end [Winne 1997; Winne 2014].

2.3. Sense-making and Exploratory Search

There are a number of challenges for self-directed learning. One of the most difficult challenges is the concept of sense-making [Butcher 2011; Miyake 2013; Rau 2012; Schoenfeld 1992]. This is the paradox that self-directed learners must utilize relatively deep thinking in order to process and absorb new information while at the same time they might not have the necessary domain knowledge in order to understand the information [Butcher 2011]. Research into self-directed learning has identified a number of different approaches used by learners in order to overcome the challenges associated with sense-making [Rovers 2018]. The concept of exploratory search is a common approach to studying self-directed learning by breaking does the problem-solving strategies into one of three different categories; selection, navigation, and trial-and-error [Chi 2009; Egusa 2010; Marchionini 2006]. With respect to self-directed learning, selection is the process of performing queries and browsing through the results, while navigation is the process of navigating through related materials, and trial-and-error is a process of repeated, variated learning attempts [Chi 2009; Marchionini 2006]. Researchers will sometimes break down the selection category based on the type of search activity; lookup, learning, and investigation [Marchionini 2006; White 2006]. Exploratory search has been used to help categorize information seeking approaches on social networks [Chi, 2009], within learning environments [Marchionini 2006], as well as in the workplace [Egusa 2010; Kules 2008; Shah 2010; Shneiderman 2007].

Studies have found that the most common type of exploratory searches fall within the lookup category [Marchionini; 2006; White 2006]; these types of searches consist of relatively basic queries focused on looking up definitions or descriptions of very specific search terms. Exploratory search of this nature has been found to be dependent on the individual in the sense that the searches performed by any given individual tend to differ both in terms of the search queries that are executed, as well as the order of searches (the "path") performed [White 2009].

Research into exploratory search has found that selective search, in which users actively make decisions about which results to include or exclude based on relevance, can significantly improve the user's mental map of the topic [Egusa 2010; White 2006]. Having a strong mental map of a topic can improve the overall knowledge of the topic, but it also improves the understanding of the individual components of the topic and how they relate to one another. This is important not just for building up deep knowledge of a topic, but also for understanding, at a high level, the breadth of a topic [Egusa 2010; White 2009].

Keyword-based searches are typically effective at well-defined information retrieval tasks where users are seeking facts of looking up definitions [Shneiderman 2007; White 2006]. These searches build on the strengths of search engines, and involve relatively simple scanning of results [Shneiderman 2007]. However, studies have found that simple keyword-based searches are less effective at more complex, less well-defined topic-based search tasks [Marchionini 2006; Shneiderman 2007]. These types of tasks are typically more open-ended and require both a broader and deeper understanding of the topic.

2.4. Information Visualization

A wide range of research has shown that the use of exploratory search in combination with information or data visualization can enhance learning when using web-based learning systems [Chi 2009; Egusa 2010; Kules 2008; Marchionini 2006; Shneiderman 2007]. Researchers have made use of social graphs [Chi 2009], concept maps [Cañas 2005; Carter-Templeton 2016; Carvalho 2001; Egusa 2010; Sebrechts 1999], categorical meta-data displays [Kules 2008; White

2006], and dynamic data displays [Marchionini 2006; Shneiderman 2007] to provide visual overviews of information in order to assist and guide learners.

Web-based concept maps can be particularly useful, as they can be made to be interactive, allowing learners to explore graph nodes (terms) and edges (relationships). Studies have found that some learners are more visually oriented, and the use of concept maps can provide a benefit for exploratory methods of learning in web-based learning scenarios [Carter-Templeton 2016; Egusa 2010]. In addition, the use of concept maps has been shown to improve learner's comprehension of relatively dense amounts of information [Cañas 2005; Daley 1999; Guthrie 2004].

Categorical visualization systems was a type of search system developed to combine search results with an overview of the metadata from the actual results themselves, allowing for improved exploration and discovery of relevant information [Kules 2008]. These systems can be further improved by clustering search results based on the relationships between those results. [White 2006]. However, implementing such systems at a large scale can be challenging, as determining whether the categories and clusters are effective, particularly when these are dynamic, requires user feedback [Marchionini 2006; White 2006].

One of the areas that visualization has helped with has been in showing relationships. Research has shown that while users typically find it relatively easy to understand the context of an individual search result, they find it significantly more challenging to map out relationships between related content [Wu 2015]. Thus, information visualization systems can significantly aide users by providing visual overviews of these relationships, providing defined pathways through the results [Carter-Templeton 2016; Wu 2015].

2.5. Individual Differences

To better understand the approaches that learners take, we need an understanding of the individual differences between learners, particularly motivation and prior knowledge [DeCaro 2015; Gabrielle 2016; Jonassen 2012]. Studies have shown that there are correlations between motivation and learning performance [DeCaro 2015; Gagné 2005; LePine 2004; Vansteenkiste 2004], thus making it important to control for these variables.

Understanding how an individual's motivations affect their approach to learning new materials can have significant impacts on how learning materials are created and put together [DeCaro 2015]. In addition, understanding the impacts of motivation can also impact the technological strategies that are used to implement and present the learning materials [Gabrielle 2016]. Studies have noted that individual differences in motivation impact how learners deal with challenges such as the sense-making paradox [DeCaro 2015], or the challenge of how to deal with new technologies [Gabrielle 2016].

Individual differences in achievement motivation have been found to have a significant influence on how learners' approach exploratory learning. Studies have shown learners with lower levels of achievement motivation have a tendency to approach learning differently, and generally receive reduced benefits from exploratory learning techniques [DeCaro 2012; Wolters 2004]. In addition, learners with lower levels of motivation have been shown to apply less sophisticated learning strategies [DeCaro 2015; Gabrielle 2016; Wolters 2004] and less effective problem-solving techniques within exploratory learning environments [DeCaro 2015].

2.6. Learning Evaluation

One additional area in which individuals can differ is with respect to how they assess their own academic work, which can have a significant outcome on motivation [Boud 2013; Sedikides 1993]. The differences between how an individual assesses their own work can have both a positive and a negative impact. It has been established that there are relationships between individual differences and how individuals self-assess their learning [Boud 2013; Kostons 2012; Panadero 2012; Taras 2015; Vialle 2015].

Studies have noted that highly-motivated, highly capable learners will self-assess themselves relatively poorly, while less-motivated learners will over-estimate their self-assessment [Andrade 2016; Dunning 2014; Kulkarni 2015]. Highly capable learners tend to be more critical of their own knowledge, skills, and abilities, while, perhaps paradoxically, less capable, less motivated learners tend to be less critical of themselves [Brown 2015; Vialle 2015]. From a confidence perspective, an individual with lower confidence in their understanding of a topic might be motivated to study the topic further, while an individual with higher confidence might be less motivated to expend as much effort studying the topic [Boud 2013; Brown 2015]. This has a number of applications for self-directed learning. Understanding the implications of self-assessments would potentially help educators better tailor learning materials to the individual, resulting in improvements to learning outcomes [Andrade 2016; Brown 2015; Kostons 2012].

Significant effort has been made to understand how to effectively measure and study self-regulated learning. There are inherent challenges in that measurements are generally obtrusive, in that they require some amount of interference into the learning process [Hadwin 2007; Winne 1982; Winne 2000]. Because of this, two of the more common unobtrusive techniques for studying self-regulated learning have involved pre- and post- learning questionnaires [Sedikides 1993; Winne 2000], as well as data logging and tracing [Hadwin 2007; Winne 1982].

One extension of the data logging and tracing approaches to studying self-regulated learning is to apply pattern matching techniques to the user activity logs, with the goal of identifying any strategies that learners are taking [Ainley 2006]. This approach has been successfully applied towards identifying sequences of user behaviors in exploratory learning environments, however, it helps to have additional information from the users or about the users, such as knowledge of individual differences, self-assessment scores, or test scores [Ainley 2006; Bannert 2014; Garcia 2012; Sha 2012]. There have been several examples of the successful application of pattern matching techniques, including the use of single-item measurements to analyze the sequencing of behaviour [Ainley 2006], the use of algorithmic clustering of trace data [Jovanović 2017], the use of t-pattern analysis to find recurring patterns [Kuvalja 2014], and a matrix-based analysis to examine the transition between behaviours in order to find patterns of event sequences [Malmberg 2014].

Chapter 3. Methodology

In this section, we describe the design of the study, the data collection process, and the analysis method performed on the collected data.

3.1. Study Design

To study the effects of individual differences and information visualization on learning strategies, we conducted a controlled design study involving students. These student participants were given the task of completing a short essay to answer two questions on a specific topic. The short-form essay nature of the task allowed for a self-directed learning exercise that would provide the minimal amount of guidance possible, giving participants the freedom to explore the topic however they wanted. Participants were provided with a web search tool and a visual concept map representing the topic, as well as several pre- and post- study questionnaires. To analyze the impacts of individual differences, participants were asked to complete Achievement Goal Orientation (AGO), Need for Cognition (NFC), and Prior Knowledge Assessment questionnaires before being provided with the task instructions and the essay questions.

Each participant was provided with a pre-generated, unique, randomly assigned, four-digit login ID and password that was used to track their activity within the web search tool and the concept map. The questionnaire and essay responses were also saved using the login ID as the database key so that they could be matched to the search and concept map activity data.

Our study consisted of guiding participants through the following steps:

1. Participants were given a general overview of the research study, their unique anonymous login ID and password, and were provided with informed consent. Participants were informed they would be able to withdraw at any point in time during the task.

2. Participants were provided with a short tutorial that guided them through the search tool and a sample concept map.

3. Participants were then asked to complete the Achievement Goal Orientation, Need for Cognition, and Prior Knowledge Assessment questionnaires.

4. Participants were given the assigned essay topic and provided with the concept map.

5. Once the participants had completed their assigned task they were asked to complete a self-evaluation questionnaire, as well as perceived usefulness questionnaires for the search tool and concept map.

Participants were provided with the tutorial (step 2) prior to the questionnaires (step 3). In the original design step 2 and 3 were reversed. However, during a trial run of the study, nearly every test participant was confused by the proximity of the tutorial concept map to the task concept map, and asked for clarification on which concept map they should use for the task. This resulted in us moving the tutorial to the start of the study, effectively reversing steps 2 and 3, and also changing the tutorial to using a very small generic concept map (see Figure 3).

Participants were recruited from two polytechnic and applied sciences post-secondary education institutions in Canada. We chose to specifically target post-secondary students as the research participants, in order to simplify the research and control the study design for knowledge, experience, and technical capability.

3.2. Research Questions and Hypothesis

Our study was designed attempting to answer the three questions and the questions were operationalized through several hypotheses.

Research Question 1. *Based on the traces of data collected following student use of both concept maps and search tools to complete an essay writing task, can meaningful learning strategies be identified and if so, what are their characteristics?*

The design of our study allows for participants to rely entirely on the concept map to complete the task, rely entirely on the search tool, or use some combination of the two tools. Research has shown that learners performing self-directed learning typically choose exploratory search tools based on familiarity [Jansen 2006; White 2009]. We expected similar results and predicted that we would find participants prefer to make use of the text-based search tool over use of the concept map, as it is a more familiar technology (hypothesis 1).

Research has also shown that learners apply different strategies when faced with information seeking tasks [White 2009], and tasks involving concept maps [Carter-Templeton 2016, Egusa 2010]. We predicted that analysis of the data traces would reveal observable patterns in the behavior of the participants as they research the topic that is provided to them (hypothesis 2).

Research Question 2. *Are the identified learning strategies associated with any post-study outcomes including essay scores?*

Research into exploratory learning has shown a correlation between the development and application of learning strategies and the learning outcomes [DeCaro 2015; Gabrielle 2016]. In addition, information visualization systems have been shown to provide learning advantages by providing visual overviews and pre-defined pathways through the topics [Carter-Templeton 2016; Wu 2015]. Given our prediction that we expect to see differentiation in the tools that the learners use (hypothesis 1) as well as observable learning strategies (hypothesis 2), we expect to see a correlation between the strategy participants employ researching the topic, and the essay scores (hypothesis 3).

Research Question 3. *Are individual differences associated with final measured outcomes?*

Research into the impacts of individual differences has shown a correlation between motivation, pre-existing knowledge, and learning outcomes [LePine 2004; Gagné 2005; Vansteenkiste 2004]. Further, it has been found that highly capable learners will self-assess themselves relatively poorly, as they tend to be more critical of their own knowledge, skills, and abilities [Andrade 2016; Dunning 2014; Kulkarni 2015]. This same research has shown that less-motivated, less-capable learners will over-estimate their self-assessment. We predicted similar results, and expected to see a correlation between motivation, prior knowledge, and final measured outcomes. Specifically, we predicted that the study would show a correlation between the relative level of motivation and the amount of time the participant will spend completing the study (hypothesis 4). Finally, we predicted a negative correlation between the relative amount of pre-existing knowledge, as measured by the pre-test questionnaire, and the amount of time the participant spends completing the task (hypothesis 5).

3.3. Topic Selection

The design of our study necessitated that we define a set of criteria to help determine the topic for the task. The topic provided to the participants needed to be relatively obscure, so that most participants would need to make use of the search tool and concept map to learn enough about the topic to answer the questions. The topic also needed to be deep enough to allow the creation of meaningful essay questions which would require more than simple definition lookup type responses. We considered several different topics, and completed three separate topic surveys, before settling on the topic and questions below.

> Please take a few minutes to explore the topics in the concept map below. Using the concept map and the search tool (menu above), write a short essay (200-300 words):
>
> - Question 1: Describe in simple language what a security exploit is.
> - Question 2: Provide an example of how a security exploit might impact a person.

3.4. Concept Map Creation and Usage

The concept map was created by following well-established principles and guidelines [Novak 2008]. First, a search for the term “security exploits” was performed using a Google Custom Search Engine (CSE) [Google 2018] that was configured to preferentially search through technology related content. At the time of the study, the free non-commercial version of Google CSE was limited to returning the top 10,000 results for a given search term [Google 2018]. A script was used to programmatically parse each page in the search results, and create a database of keywords. We limited the keywords to words consisting of more than four characters in order to filter out common English language words [Novak 2008]. A series of test concept maps was then created from the keyword database by linking together related pages based on the top keywords per page. We started by creating links based on the number of matches within the top five keywords. This produced a relatively sparse concept map, so we proceeded to increase the number of keywords, regenerating the concept map at each step and reviewing the output. At ten keywords we found that the concept map was too dense, with too many overlapping links to easily read and navigate. We began reducing the number of keywords, until we settled on the top eight keywords, at which point we reached a reasonable link density between concept map nodes, balancing the number of interlinks with ease of readability and navigability.

When a user clicked on a term within the concept map, rather than seeing multiple pages leading to thousands of search results, as is common in search engines, the user interface would display a set of links the pages for that particular term, based on the ranking of the related keywords in the database of keywords. Similarly, clicking on the cross-link between two terms would display a set of links to the top 50 web pages for that particular cross-link, based on a ranking of the cross-links between the two terms.

3.5. Research Tool User Interface

The research tool used by the participants in the study was a website consisting of nine sequential pages that the participants had to step through, as well as two popup windows containing the tutorial pages for the concept map and search tool (Figures 1 through 11 below). The research tool website was hosted on the Microsoft Azure cloud services website at the http://searchapp.net domain name.

The research tool pages consist of the login page, with research consent form (Figure 1), the tutorial pages (Figures 2 through 4), the pre-test questionnaire pages (Figures 5 through 7), the essay entry form and concept map page (Figure 8), the post-test questionnaire pages (Figure 9 and 10), and the final completion and logout page (Figure 11).

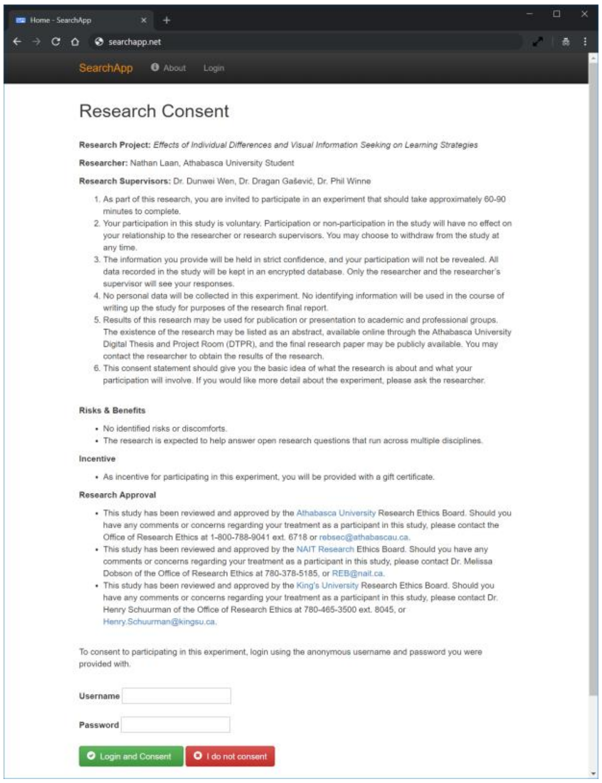


Figure 1. Research Tool Landing Page.

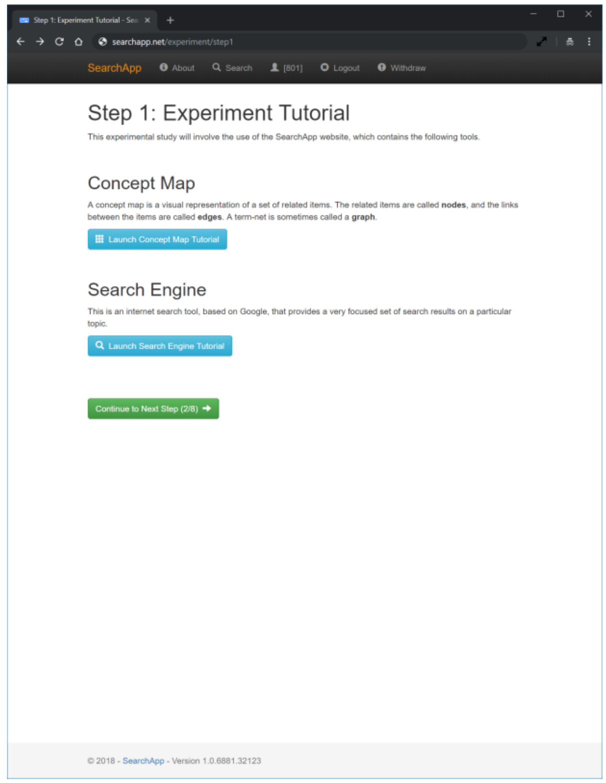
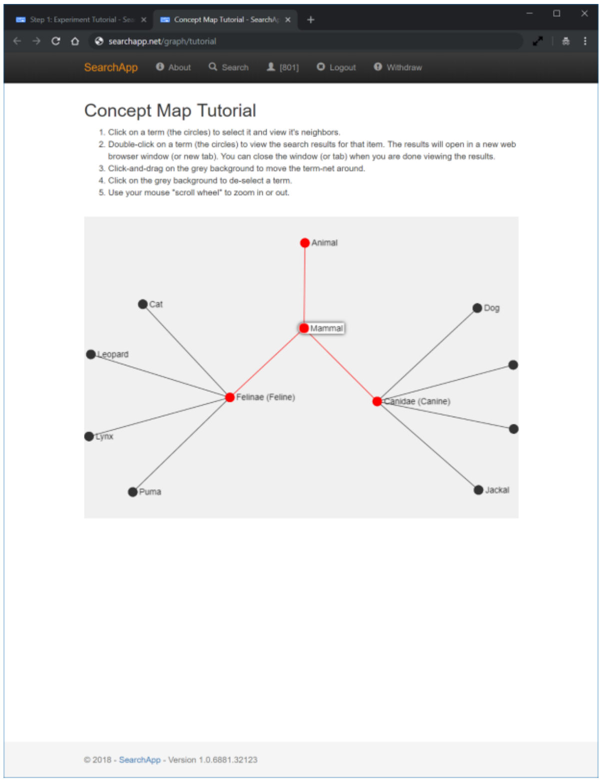


Figure 2. Research Tool Tutorials.



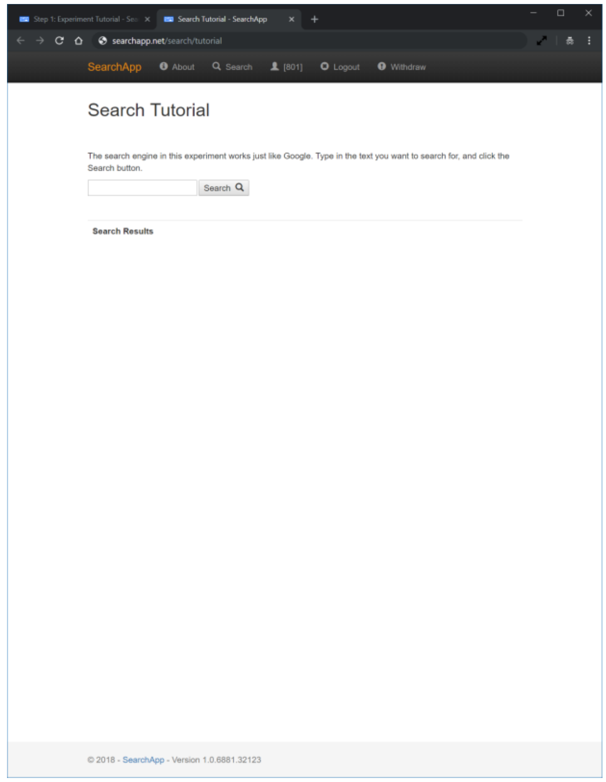


Figure 3. Research Tool Concept Map Tutorial. *Figure 4*. Research Tool Search Tool Tutorial.

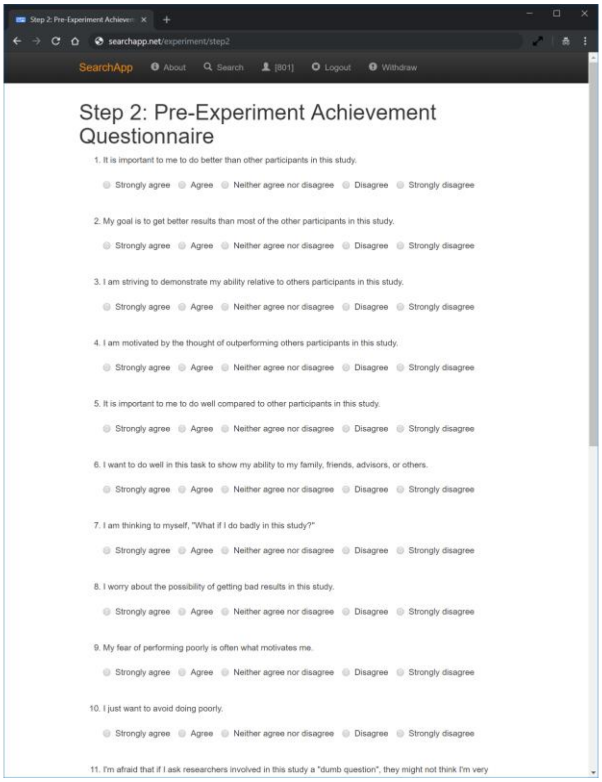
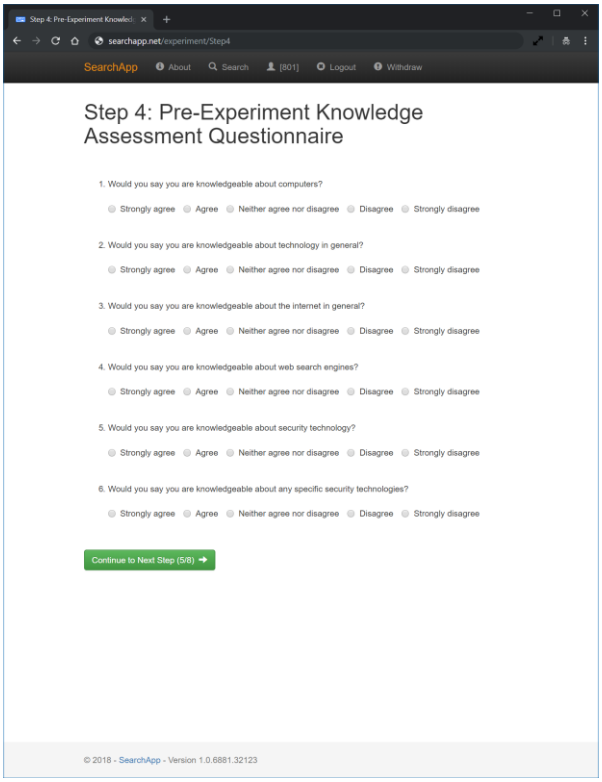


Figure 5. Research Tool AGO Questionnaire.

Figure 6. Research Tool NFC Questionnaire.



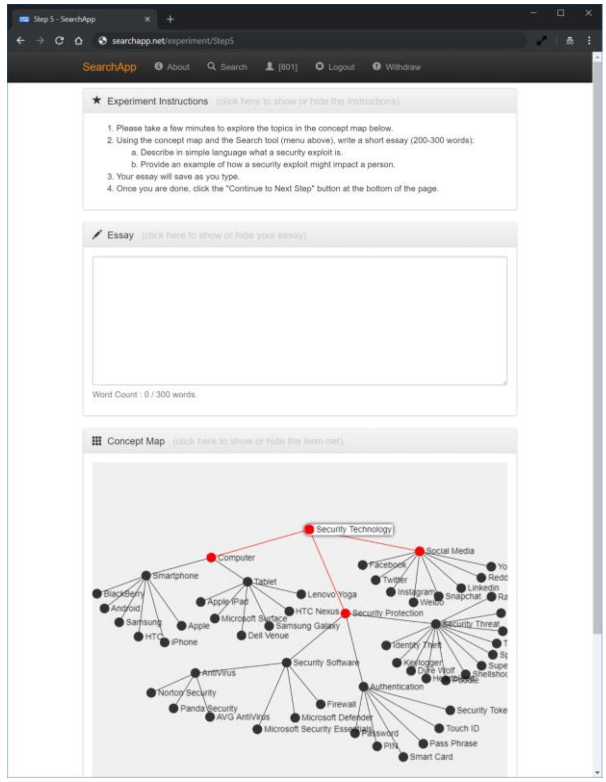


Figure 7. Research Tool PKA Questionnaire.

Figure 8. Research Tool Essay Entry Form.

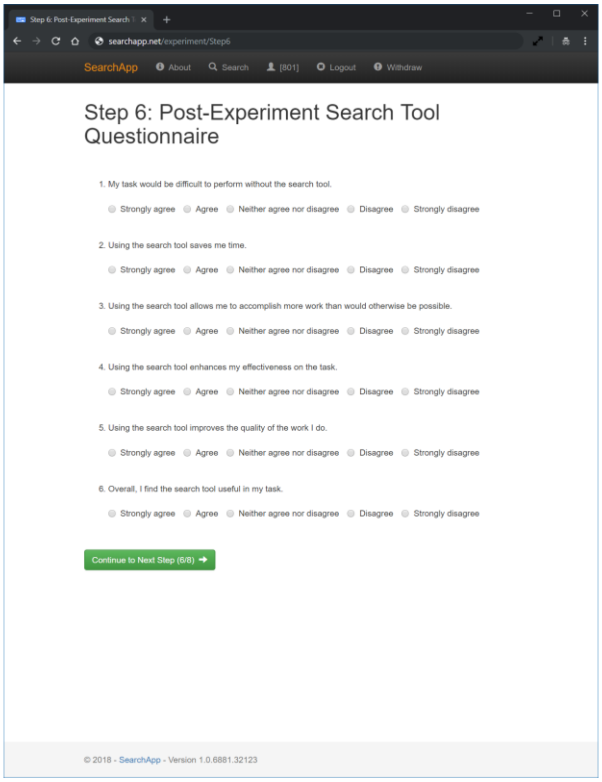


Figure 9. Research Tool PUST Questionnaire.

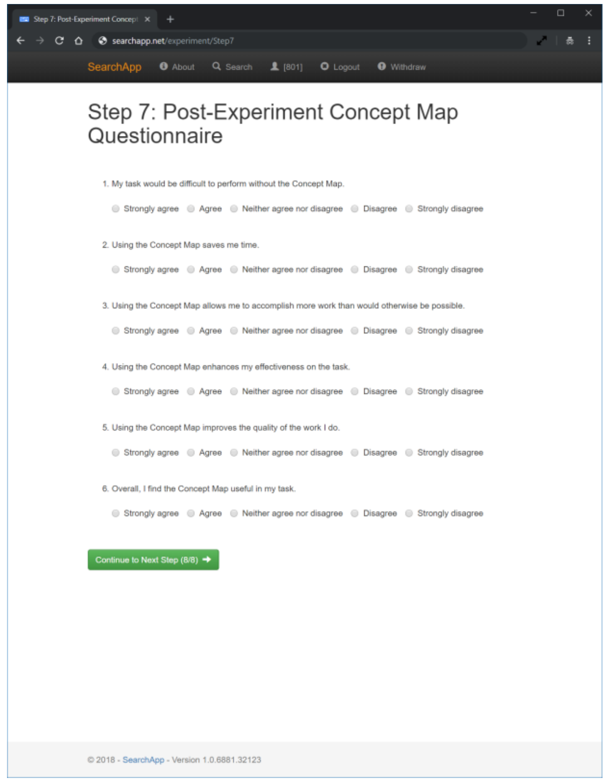


Figure 10. Research Tool PUCM Questionnaire.

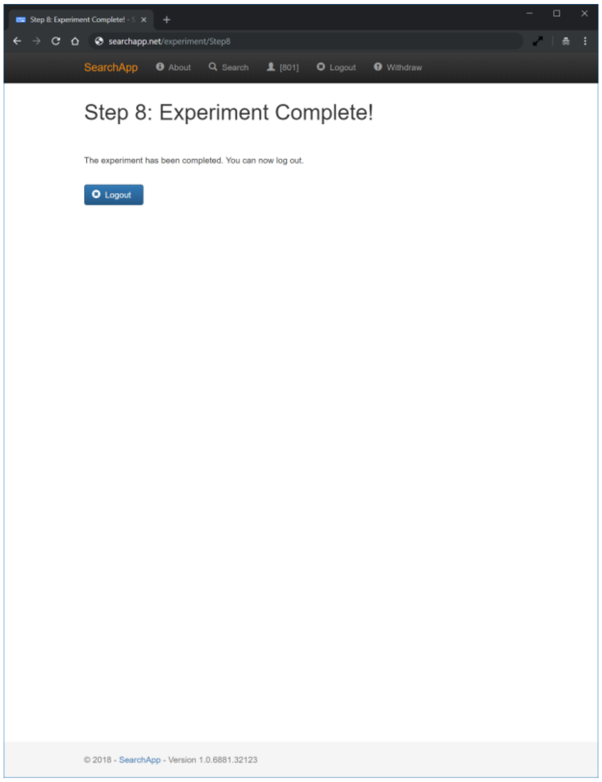


Figure 11. Research Tool Completion Page.

3.6. Data Collection and Questionnaires

A primary focus of the research was to measure the effects of individual differences relative to performance, as well as relative to perceived performance. In order to accomplish this, pre- and post-test questionnaires were provided to the research participants, in order to measure the following individual differences.

- Pre-existing knowledge
- Motivation to demonstrate knowledge and skills to others
- Motivation to avoid poor performance
- Motivation to develop knowledge and skills
- Need for cognition

User navigation data was captured using web tracing techniques, a common, well-established technique for tracking and analyzing a user's web browsing and web searching activities [Hadwin 2007]. It consists not only of looking at the web pages that a user views, but also looking at the time spent on each page before navigating away [Hadwin 2007; Winne 1982; Winne 2000]. In this way, an estimate of the amount of time spent on a given page can be inferred.

For our study, we were specifically interested in capturing the number of searches run, the number of search pages viewed, the number of concept map terms viewed, and the total time on task for each participant.

To log this data, it is necessary to either instrument each participant’s web browser to record web history or require each participant to complete their activity on a specific website where their actions can be logged. However, because we had limited control over the laboratory environment where our study was run, we chose the strategy of implementing a web-based application that the participants would log into and run through the entire study from start to finish.

Participants were provided with a web-based search application based on the Google Custom Search Engine (CSE) technology. This allowed the search queries, page views, and page view times to be precisely logged for each participant. Because the study relied on facilities where we had limited control over the computer equipment, the web-based application allowed capturing data with a higher level of detail than would otherwise be possible.

Each log entry is composed of an automatically assigned numeric event id, the login id assigned to the participant, the action being performed (searching, viewing a web page, clicking a link in the concept map, etc.), and a timestamp.

In addition to the log data, data from several pre- and post-test questionnaires was collected. To identify the Individual Differences between the participants, several standard pre- and post- study instruments have been developed. These include instruments for motivation, aptitude, cognitive styles, self-regulation, and personality traits [Jonassen 2012; Winke 2007]. A number of these instruments have close associations with research into education and learning, and have been used to study self-regulated learning as well as exploratory learning. The Achievement Goal Orientation (AGO) questionnaire is an instrument used to assess motivation and has seen use in numerous education and learning research studies [Finney 2004; Howell 2007; Midgley 1998]. The AGO questionnaire consists of a standard set of questions [Finney 2004; Howell 2007; Midgley 1998] that are used to assess the factors that drive an individual's motivation, as well as provide an overall measure of the relative level of motivation [Finney 2004; Midgley 1998; Midgley 2014]. The questions were customized to match the nature of the study, by replacing general language with specific language that references "the participants" and "the study".

The AGO questionnaire is broken down into three categories of questions. The first group, AGOG1, deal with individual motivation to demonstrate capability and knowledge to others. The second group, AGOG2, are focused on motivation to avoid demonstrating poor performance. The third and final group, AGOG3, deal with the goal of developing knowledge or capability. AGOG1 is sometimes referred to as ability-approach goal orientation, AGOG2 is sometimes referred to as ability-avoid goal orientation, and AGOG3 is sometimes referred to as task goal orientation [Midgley 1998; Midgley 2014].

The Need for Cognition (NFC) questionnaire is similar to the AGO questionnaire in that it measures motivation, however, it focuses on assessing the need for intellectual challenge rather than achievement [Cacioppo 1996; Cohen 1955; Evans 2003]. The Need for Cognition questionnaire is an assessment instrument used to measure the tendency for an individual to enjoy and engage in thinking activities [Cacioppo 1982]

Knowledge assessment questionnaires are standardized instruments designed to help control for pre-existing knowledge. A knowledge assessment questionnaire was provided to participants in order to provide for a measure of pre-existing knowledge relating to the assigned essay topic.

The perceived usefulness questionnaire is a standardized set of questions that were designed to allow users to provide feedback on how useful, easy to use, and productive they find a particular information technology [Adams 1992; Davis 1989]. For our study, we used two Perceived Usefulness questionnaires, one to allow participants to evaluate the perceived usefulness of the concept map, and the other to evaluate the Google Custom Search Engine (CSE).

The self-evaluation questionnaire is a simple instrument designed to study how learners rate the answers they have provided on a given task [Sedikides 1993]. In order to investigate how users perceived their own performance, a post-test self-evaluation questionnaire was provided to participants for them to rate their answers to the essay questions.

3.7. Essay Grading Rubric

Having a straightforward and easy to understand grading rubic is essential to ensuring that the scoring of the essays remain relative to the same baseline, and as unbiased as possible [Andrade 2005; Brookhart 2014; Jensen 1995; Stevens 2013]. There are two types of rubrics; holistic and analytical [Mertler 2001]. Holistic rubrics are suitable when scoring an overall item as a whole, and the individual components are not as important, while analytical rubrics are suitable when scoring the individual components is important [Mertler 2001; Moskal 2000]. Within these two types, there are a couple of difference approaches to scoring the rubric or the components of the rubric. The three most common approaches include percentage-based, points-based, and pass/fail styles of grading [Moskal 2000; Trice 2000].

We selected an analytical type rubric, with a pass/fail style of grading. This would allow us to evaluate the components of the essay if needed, while keeping the essay grading as simple as possible. We followed the seven-step process for developing rubrics [Mertler 2001], and arrived at the model shown below in *Table 1*.

Table 1

Essay Grading Rubric

Question	Factor	0 Points	1 Point
1	Facts	Absent or Wrong	Present & Accurate
2	Facts	Absent or Wrong	Present & Accurate
2	Question #2 Argument	Confusing or Weak	Logical & Clearly Articulated
2	Question #2 Coherence	Inadequate	Purposeful and Organized

For essay question 1, our grading rubric considered only whether the learner provided an accurate and reasonable definition of what a security exploit is. For essay question 2, our grading rubric gave one point awarded for each accurate factual example of a possible security exploits, and 1 additional point for a logical and clearly articulated argument for how the example could impact a person. Finally, our grading rubric gave one point overall for a purposeful and organized answer to essay question 2.

The essay scoring process was completed by the researcher, prior to viewing any other participant data. The essays were scored once in a random order, and then each essay score was reviewed and validated by the researcher a second time, again in random order.

3.8. Statistical Analysis

To address research question one, which aimed to identify and characterize the learning strategies used by students during an essay writing task, event sequence analysis was carried out using the TraMineR package in R [Gabaldinho 2011]. For each student participating in the study, trace data was collected during the time engaging with both the concept map and search tool, which corresponded to one of four actions: View-Search-Link, Perform-Search, View-Term, and View-Term-Link ; these were the events to be analyzed. As the aim was to explore the learning strategies enacted by students, the overall event sequences were initially plotted as a means of visualizing how student actions vary over the course of the essay writing task. This visualization of the event sequences was then supplemented with descriptive statistics showing the frequency at which the sample of students engaged in each record action; in addition to details about Time-On-Task.

Based on prior work that showed students to be heterogeneous with regards to their learning strategies [Matcha 2019], we sought to segment the event sequences using agglomerative hierarchical cluster analysis. The decision to use agglomerative hierarchical cluster analysis was based on the reasons outlined by Kovanović, Gašević, Joksimović, Hatala, and Adesope [Kovanović, 2015]: cluster solutions are small so the use of dendrograms can be manageable, and it performs well with small data sets. The hierarchical clustering criterion used in this work was Ward's method, which was applied to the distance matrix created using optimal matching with an insertion/deletion cost of 1, again this is in line with prior work [Fincham, 2018]. When deciding upon the cluster solution to use, we also considered the interpretability of the clusters as a means of determining what is an appropriate cut-off.

Following the identification of a suitable cluster solution, the differences between the identified clusters were explored through descriptive statistics, representative sequence plots, and Markov models. The descriptive statistics were frequency measures for each of the four recorded actions (View-Search-Link, Perform-Search, View-Term-Link, and View-Term). The representative sequences are a series of bars plotted in relation to their representativeness score, with bar width representing the number of sequences being assigned (i.e., wider bars represent a larger number of sequences being assigned to that representative). For the purposes of this work, the expected coverage of the representative set was set at 25%. This means that at least 25% of the original sequences should have a representative within their neighbourhood. Thus, for each cluster there may be different numbers of representatives for the 25% threshold to be met. The representative plots were used to provide additional details on how the identified clusters differed with regards to the actions undertaken during the essay writing task. The Markov models were fitted to each identified cluster using the seqhmm package in R with no hidden structure being specified. In order to present the information back, plots were created that provide details on the initial state probability and transition probabilities. This information allowed the researchers to further understand how students within the clusters changed between actions during the course of the essay writing task.

As for understanding the characteristics of any identified groups of students, they will be compared across the pre-study measures collected (need for cognition, ability-approach goal orientation, ability-avoid goal orientation, task goal orientation, and perceived prior knowledge). Average scores were computed for each of these five aforementioned variables for the purposes of comparing the identified student groups using t-tests. In addition, logistic regression was used with cluster assignment being regressed onto the five pre-study predictor variables.

To address research question two, which sought to explore whether the identified learning strategy groups differed in regards to six post-study variables (Time-On-Task, essay score, perceived usefulness of the concept map, perceived usefulness of the search tool, perceived essay answer accuracy, and perceived essay answer validity). Four of these variables (perceived usefulness of the concept map, perceived usefulness of the search tool, perceived essay answer accuracy, and perceived essay answer validity) were created on the basis of an average score across the items previously reported as loading onto these factors. As with research question one, t-tests will be used to compare the identified clusters across each of the six post-study variables.

Research question three aimed to explore whether the four learning actions (View-Search-Link, Perform-Search, View-Term, and View-Term-Link), motivations, and perceived prior knowledge are associated with four post-study outcomes (perceived usefulness of the concept map, perceived usefulness of the search tool, perceived essay answer accuracy, and perceived essay answer validity). To address this question, four linear regression models were ran with each of the four aforementioned post-study variables being regressed onto six predictor variables (cluster assignment, need for cognition, ability-approach goal orientation, ability-avoid goal orientation, task goal orientation, and perceived prior knowledge). For the purposes of this current work, the alpha level was set at .05.

Chapter 4. Results

The goal of this study was to investigate the effects of individual differences on exploratory learning in a self-directed learning environment. We provided a visual concept map, as well as a text-based search engine, provided a task in the form of completing a short essay, and then investigated the effects of individual differences. We sought to understand the impacts of prior knowledge, as well as motivation using Achievement Goal Orientation.

A total of 138 participants were solicited at the North American Institute of Technology (NAIT) and Kings University campuses in Edmonton, Alberta over a period of five days. Of these, 17 participants withdrew from the study before completion. A total of 111 participants completed the study and submitted completed essays and questionnaires. The remaining 10 participants submitted blank essay responses. Only the data from the 111 completed submissions was included in the analysis.

Printed posters as well as informational postings on the intranet websites for the two institutions were used to generate awareness and recruit participants. During the study, the researcher also walked around the campuses, verbally recruiting participants, and handing out printed leaflets to students in order to generate awareness. Participants that completed the study were offered a C$10 gift card for a local coffee shop as incentive. The participants were free to explore and make use of the learning materials, search tool, and concept map according to their individual preference.

The concept map activity logs, web search logs, and questionnaire data for each participant were exported from the online database into a CSV file that was then loaded into the RSTUDIO version 1.0 tool for analysis using the R version 3.3.2 statistical programming language. We examined a total of 24 variables, outlined in *Table 2* below.

Table 2

Overview of Variables

Variable	Description	Type
AGO	Pre-test Achievement Goal Orientation questionnaire (total)	Ordinal
AGOG1	Pre-test questionnaire (Ability Approach Goal Orientation)	Ordinal
AGOG2	Pre-test questionnaire (Ability Avoid Goal Orientation)	Ordinal
AGOG3	Pre-test questionnaire (Task Goal Orientation)	Ordinal
NFC	Pre-test Need for Cognition Questionnaire	Ordinal
NFCG1	Pre-test Group 1 questions on NFC questionnaire	Ordinal
NFCG2	Pre-test Group 2 questions on NFC questionnaire	Ordinal
NFCG3	Pre-test Group 3 questions on NFC questionnaire	Ordinal
PKA	Pre-test Prior Knowledge Assessment questionnaire	Ordinal
PKAG1	Pre-test Group 1 questions on PKA questionnaire	Ordinal
PKAG2	Pre-test Group 2 questions on PKA questionnaire	Ordinal
PKAG3	Pre-test Group 3 questions on PKA questionnaire	Ordinal
PUCM	Post-test Perceived Usefulness Concept Map questionnaire	Ordinal
PUST	Post-test Perceived Usefulness Search Tool questionnaire	Ordinal
SEQ1	Post-test Self Evaluation for essay question 1	Ordinal
SEQ2	Post-test Self Evaluation for essay question 2	Ordinal
Time-On-Task	Total time completing task	Continuous
Searches	Total number of searches performed (Corresponds to Perform-Search action)	Continuous
Search Links	Total number of search links viewed (Corresponds to View-Search-Link action)	Continuous
Terms	Total number of concept map terms viewed (Corresponds to View-Term action)	Continuous
Term Links	Total number of concept map term links viewed (Corresponds to View-Term-Link action)	Continuous
EssayScore	The total essay score	Continuous
EssayScore1	The score for essay question 1	Continuous
EssayScore2	The score for essay question 2	Continuous

4.1. Analysis

Research Question 1. Based on the traces of data collected following student use of both concept maps and search tools to complete an essay writing task, can meaningful learning strategies be identified and if so, what are their characteristics?

The essay task times ranged from 445 seconds to 4843 seconds with an average completion time of 1998.883 seconds (SD = 1451.904 seconds; a distribution of these times is presented in Appendix). Table 3 presents the counts and percentages for each of the four actions captured in the log data (View-Search-Link, Perform-Search, View-Term-Link, and View-Term). As can be seen from Table 3, View-Term-Link was the most common action, occurring 55.20% (n = 5280) of the time. This was then followed by View-Search-Link (n = 2217, 23.20%), View-Term (n = 1331, 13.90%), and then Perform-Search (n = 741, 7.74%).

Table 3

Action Counts and Percentages

Action	n	%	M	SD
Searches (Perform-Search)	741	7.74	6.68	4
Search Links (View-Search-Link)	2217	23.20	20	3
Terms (View-Term)	1331	13.90	12	7
Term Links (View-Term-Link)	5280	55.20	47.60	12

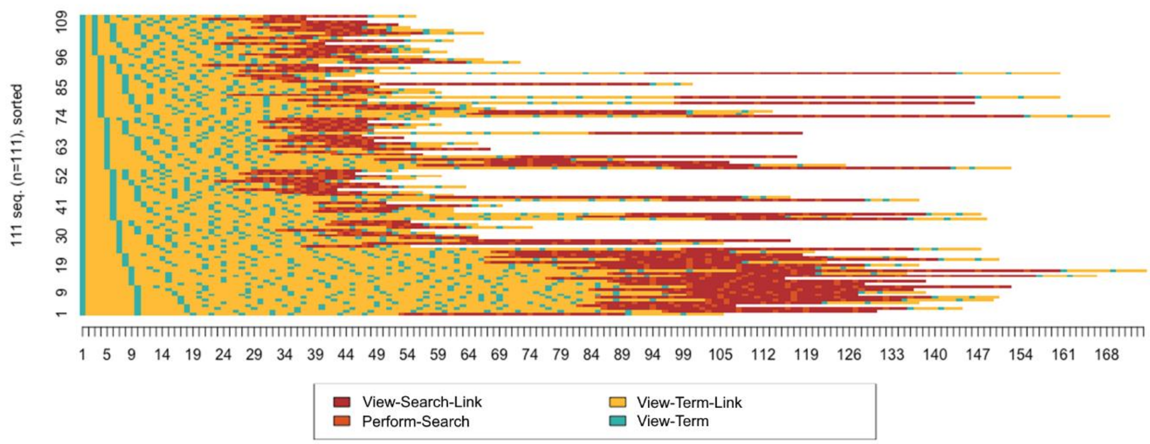


Figure 12. Plot of Event Sequences for the Whole Sample (n = 111).

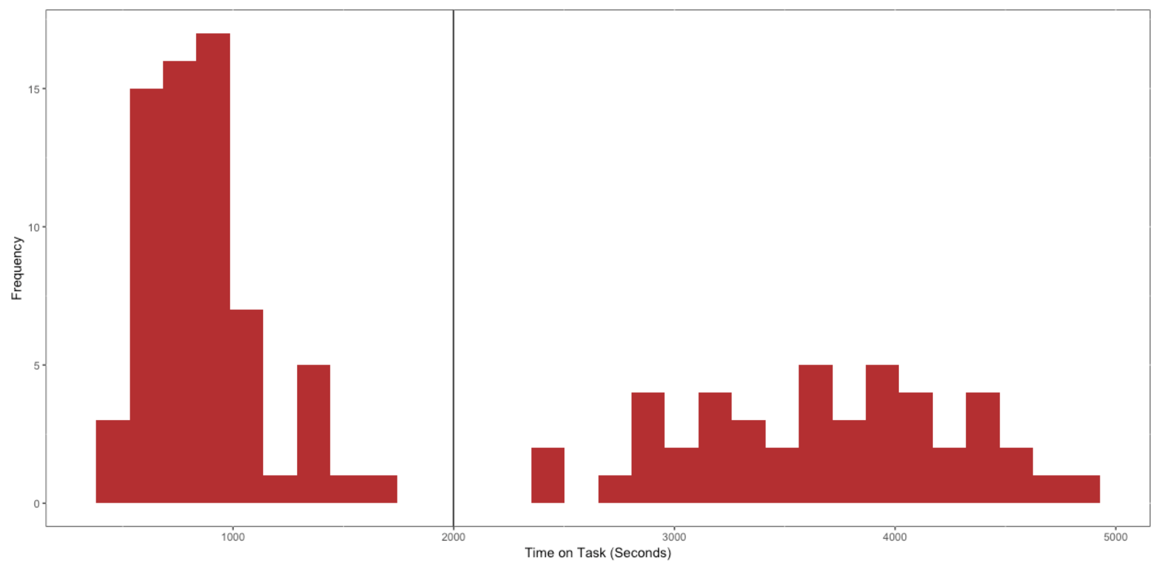


*Figure 13***.** Distribution of Time-On-Task in Seconds (Line represents the mean time).

Based on both the plot of actions used during the essay writing task (Figure 12) and the distribution of Time-On-Task (Figure 13), it could be argued that students were not homogenous in their learning strategies. To explore whether these learning strategies were heterogeneous, the next step was to analyze the event sequences using hierarchical cluster analysis. In order to run this analysis, a dissimilarity matrix was created using the optimal matching method and a substitution cost of 1.

The dendrogram for the hierarchical clustering analysis is presented in Figure 14, which shows a two-cluster solution to be a suitable cut-off. To determine whether the two-cluster solution was interpretable, a representative sequence plot was used to explore how the two groups differed (Figure 15). Based this plot, the first group (left plot in Figure 15) was assigned the label the High Engagement Group as the event sequences were long in length. Whereas, the second group (right plot in Figure 15) was labelled the Low Engagement group given the short sequence lengths defining the cluster. The High Engagement group was made up of 45 students and was represented by 12 event sequences, which gave a 26.70% coverage (Figure 15). These 12 event sequences showed that the High Engagement students initially started with a View-Term action, which was then followed by a pattern of changing between the View-Term and View-Term-Link actions. It was only towards the end of the event sequences that the High Engagement group started to display the Perform-Search and View-Search-Link actions. The Low Engagement group, on the other hand, included 66 students and was represented by a single event sequence that gives a 30.30% coverage (Figure 15). Although different in sequence length, when compared to the High Engagement group, the Low Engagement group representative sequence was similar. The representative sequences indicated students initially switched between the actions of View-Term and View-Term-Link. Then, towards the end of the event sequence, students then began to engage in Perform-Search and View-Search-Link actions.

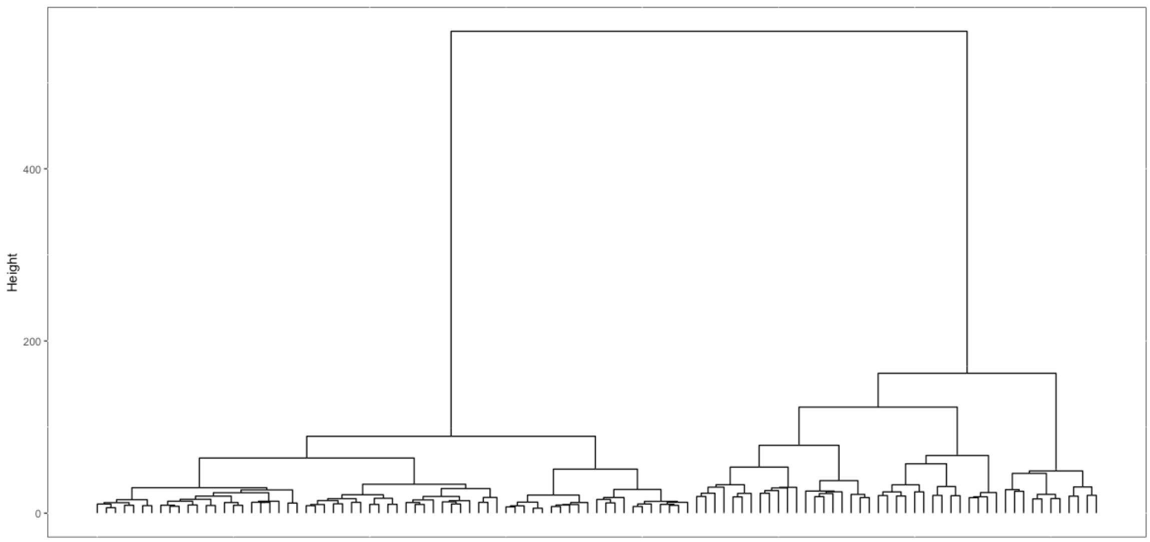


Figure 14. Dendrogram Obtained from the Hierarchal Cluster Analysis using the Dissimilarity Matrix.

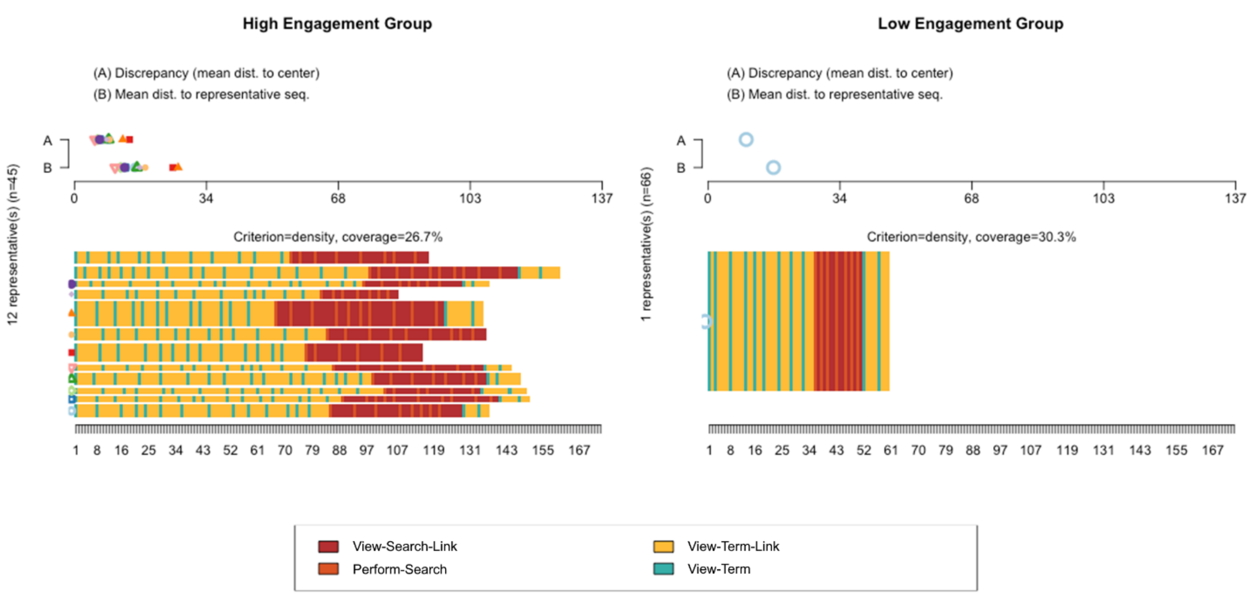


Figure 15. Representative Sequence Plots for the Two-Cluster Solution.

Descriptive statistics for the two groups (High Engagement and Low Engagement) are presented in Table 4, which gives a more detailed understanding as to why they differ. For both groups, the most common action within the essay writing task was View-Term-Link, which made up 56.20% (n = 3340) and 53.60% (n = 1940) of actions for both the High and Low Engagement groups, respectively. In addition, the View-Term-Link action occurred, on average, 74.20 times (SD = 15.20) for the High Engagement group and 29.40 times (SD = 7.65) for the Low Engagement group. The second most frequent action event was View-Search-Link for the High Engagement group (M =35.40, SD = 7.41, n =1595, 26.80%), whilst for the Low Engagement group it was View-Term (M = 10.20, SD = 1.41, n = 672, 18.60%). The third most frequent action for the High Engagement group was View-Term (M = 14.60, SD = 2.60, n = 659, 11.10%) and for the Low Engagement group it was View-Search-Link (M = 9.42, SD = 2.50, n = 622, 17.20%). Finally, Perform-Search was the least frequent action for both the High Engagement group (M = 7.84, SD =1.59, n = 353, 5.94%) and Low Engagement group (M = 5.88, SD = 1.14, n = 388, 10.70%). Taking the abovementioned points on coverage and descriptive profiles, the two-cluster solution was deemed to be interpretable and therefore considered as a suitable cut-off for the current work.

Table 4

Descriptive Statistics for High and Low Engagement Groups

Variable	High Engagement Group				Low Engagement Group			
	n	%	M	SD	n	%	M	SD
Searches (Perform-Search)	353	5.94	7.84	1.59	388	10.70	5.88	1.14
Search Links (View-Search-Link)	1595	26.80	35.40	7.41	622	17.20	9.42	2.50
Terms (View-Term)	659	11.10	14.60	2.60	672	18.60	10.20	1.41
Term Links (View-Term-Link)	3340	56.20	74.20	15.20	1940	53.60	29.40	7.65
Time-On-Task*	-	-	3618.93	613.54	-	-	831.77	242.97
Ability-Approach Goal Orientation	-	-	2.85	.81	-	-	3.04	1.03
Ability-Avoid Goal Orientation	-	-	2.87	.98	-	-	3.01	1.14
Task Goal Orientation	-	-	2.84	1.11	-	-	3.04	1.12
Need for Cognition	-	-	4.08	.17	-	-	4.07	.17
Perceived Prior Knowledge	-	-	3.40	.46	-	-	2.58	.56
Perceived Usefulness of Concept Map	-	-	3.76	.37	-	-	3.90	.32
Perceived Usefulness of Search Tool	-	-	3.75	.37	-	-	3.70	.39
Perceived Essay Answer Accuracy	-	-	4.42	.66	-	-	4.38	.65
Perceived Essay Answer Validity	-	-	3.80	.73	-	-	3.89	.64

*Mean and standard deviation values refer to seconds

The next step of the analysis was to explore how students within these two clusters moved between different observed states using a first-order Markov model. Figure 15 presents the first-order Markov models for the two cluster (the High and Low Engagement groups) and the transition matrices are in Appendix C. For both Markov models, students in both clusters started their tasks with the View-Term action and all then switched to the View-Term-Link action. For those in the High Engagement group, there was an .810 probability of continuing with the View-Term-Link action, which reduced to .669 for the Low Engagement group. When switching from the View-Term-Link action back to the View-Term action, the Low Engagement group had a higher transition probability (.296) than the High Engagement group (.176). As for switching from either the View-Term action to the Perform-Search or View-Search-Link actions, the transition probabilities were 0 for both the High and Low Engagement groups. As for transitioning from the View-Term-Link action to either the Perform-Search or View-Search-Link actions, the transition probabilities were low for the High (.014 and .000, respectively) and Low (.035 and .000, respectively) Engagement groups.

As for moving from the Perform-Search action to the View-Search-Link action, there was a transition probability of 1 for students of the High Engagement group; whereas, the probability of remaining in Perform-Search state was 0. In the case of the Low Engagement group, the transition probability from the Perform-Search to the View-Search-Link was .852, whilst the probability of remaining in the Perform-Search state was .130. With regards to transition probabilities for changing from the Perform-Search action to either the View-Term or View-Term-Link, these were 0 for the High Engagement group; the Low Engagement group had transition probabilities of 0 and .018 for the View-Term-Link and View-Term, respectively. Finally, with regards to the View-Search-Link action, the High Engagement group had transition probabilities of .786, .195, 0, and .020 for View-Search-Link, Perform-Search, View-Term-Link, and View-Term, respectively. Whereas, for the Low Engagement group, the transitions probabilities from the View-Search-Link to View-Search-Link, Perform-Search, View-Term-Link, and View-Term were .486, .451, 0, and .063, respectively.

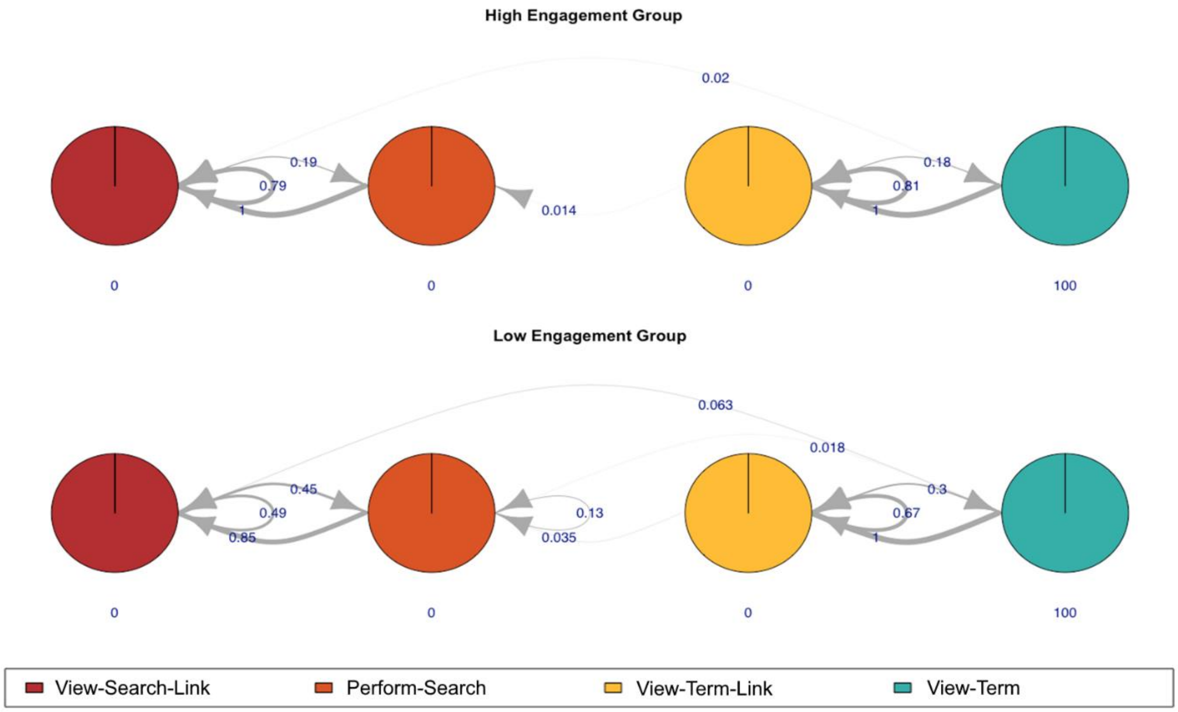


Figure 16. Markov Model Plots for the High and Low Engagement Groups.

To explore how the two identified clusters (High and Low Engagement group) differed regarding background characteristics (need for cognition, ability-approach goal orientation, ability-avoid goal orientation, task goal orientation, and perceived prior knowledge), five comparisons were made. For the need for cognition variable, it was found that students in the High Engagement group (M = 4.08, SD = .17) and Low Engagement group (M = 4.07, SD = .17) did not significantly differ from one another; t(95.08) = -.37, p = .71, d = .07. There was no significant difference between the High (M = 2.85, SD = .81) and Low (M = 3.04, SD = 1.03) Engagement groups with regards to ability-approach goal orientation; t(106.63) = 1.07, p = .29, d = .20. Similarly, neither group significantly differed with regards to both the ability-avoid goal orientation (High Engagement group: M = 2.87, SD = .98; Low Engagement group: M = 3.01, SD

$= 1.14$; $t(103.19) = .65$, $p = .52$, $d = .12$) or task goal orientation (High Engagement group: $M = 2.84$, $SD = 1.11$; Low Engagement group: $M = 3.04$, $SD = 1.12$; $t(95.65) = .89$, $p = .38$, $d = .17$) variables. As for perceived prior knowledge, the High Engagement group ($M = 3.40$, $SD = .46$) had a significantly higher score than the Low Engagement group ($M = 2.58$, $SD = .56$); $t(105.43) = -8.34$, $p < .001$, $d = 1.58$.

Research Question 2. Are the identified learning strategies associated with any post-study outcomes including essay scores?

The two clusters identified based on the event sequences were then compared based on their time spent on the essay task (Time-On-Task) and their final essay grade using t-tests. The average essay marks for the High Engagement group ($M = 8.89$, $SD = 1.54$) were significantly different from the Low Engagement group ($M = 3.80$, $SD = 2.37$); $t(108.81) = 13.706$, $p < .001$, $d = 2.55$. As for the time-on-task, the High Engagement group ($M_{Seconds} = 3670.07$, $SD = 613.61$) were significantly different from the Low Engagement group ($M_{Seconds} = 859.44$, $SD = 246.44$); $t(53.77) = 29.165$, $p < .001$, $d = 6.01$.

Comparisons between the two groups (High and Low Engagement), were also made on the four post-study variables (perceived usefulness of the concept map, perceived usefulness of search tool, perceived essay task accuracy, and perceived essay task validity). The findings showed the Low Engagement group ($M = 3.90$, $SD = .32$) to have a significantly higher score for perceived usefulness of the concept map than the High Engagement group ($M = 3.76$, $SD = .37$); $t(85.04) = 2.10$, $p = .04$, $d = .41$. As for the remaining variables, there were no significant differences between the two groups on perceived usefulness of the search tool (High Engagement group: $M = 3.75$, $SD = .37$; Low Engagement group: $M = 3.70$, $SD = .39$; $t(98.08) = -.64$, $p = .52$, $d = .12$), perceived essay task accuracy (High Engagement group: M = 4.42, SD = .66; Low Engagement group: M = 4.38, SD = .65; t(94.09) = -.34, p = .73, d = .07), and perceived essay task validity (High Engagement group: M = 3.80, SD = .73; Low Engagement group: M = 3.89, SD = .64; t(86.08) = .70, p = .48, d = .14).

Cluster assignment, with the Low Engagement group as the baseline, was then regressed on five predictor variables (ability-approach goal orientation, ability-avoid goal orientation, task goal orientation, need for cognition, and perceived prior knowledge). The output of the logistic regression model is presented in Table 5, which only shows that a one-unit increase in perceived prior knowledge being associated with an increase in log odds of being assigned to the High Engagement group by 3.144 units. Put differently, students with higher perceived prior knowledge were more likely to be in the High Engagement group. No other predictor variable was found to be associated with cluster assignment at the 5% level.

Table 5

Coefficient for Logistic Regression Model Predicting the Probability of Cluster Assignment

Variable	Estimate	Standard Error	Z Value	P-Value
Intercept	-19.797	7.525	-2.631	.009
Ability-Approach Orientation	-.581	.678	-.857	.391
Ability-Avoid Goal Orientation	.232	.575	.403	.687
Task Goal Orientation	-.338	.530	-.637	.524
Need for Cognition	2.956	1.693	1.746	.081
Prior Knowledge	3.144	.584	5.386	< .001

Research Question 3. Are individual differences associated with final measured outcomes?

Four dependent variables (perceived usefulness of the concept map, perceived usefulness of the search tool, perceived essay answer accuracy, and perceived essay answer validity) were regressed onto nine predictor variables (View-Search-Link, Perform-Search, View-Term-Link, and View-Term, ability-approach goal orientation, ability-avoid goal orientation, task goal orientation, need for cognition, and perceived prior knowledge). For all regression models ran, the F-statistics were smaller than 1, all p-values exceeded .05, and adjusted R2 values approximately equaled 0. The outputs of the four regression models are presented in Tables 6 to 9. Tables 18 and 19 show the results of the correlation matrix analysis. The F-statistics, calculated using the RCORR function in the HMISC library in R, for both perceived prior knowledge (PKA) and time-on-task, as well as time-on-task and essay score, showed a p-value less than .05. This indicates a positive correlation between perceived prior knowledge and time-on-task, and between time-on-task and essay score (Table 19).

Table 6

Linear Regression Model Predicting Perceived Usefulness of the Concept Map

Variable	Estimate	Standard Error	T Value	P-Value
Intercept	3.664	.929	3.943	<.001
Searches (Perform-Search)	-.018	.037	-.476	.635
Search Links (View-Search-Link)	.004	.008	.581	.562
Terms (View-Term)	.025	.036	.698	.487
Term Links (View-Term-Link)	-.006	.006	-.999	.320
Ability-Approach Orientation	-.007	.088	-.079	.937
Ability-Avoid Goal Orientation	-.053	.070	-.760	.449
Task Goal Orientation	.054	.071	.754	.452
Need for Cognition	.084	.205	.408	.684
Prior Knowledge	-.047	.074	-.645	.520
Multiple R^2: .045		Adjusted R^2: -.040		
$F(9, 101) = .528$, $p = .851$				

Table 7

Linear Regression Model Predicting Perceived Usefulness of the Search Tool

Variable	Estimate	Standard Error	T Value	P-Value
Intercept	2.283	1.005	2.272	.025
Searches (Perform-Search)	.064	.040	1.579	.117
Search Links (View-Search-Link)	-.007	.008	-.794	.429
Terms (View-Term)	-.012	.038	-.304	.762
Term Links (View-Term-Link)	.002	.006	.345	.731
Ability-Approach Orientation	-.080	.095	-.841	.402
Ability-Avoid Goal Orientation	.062	.076	.820	.414
Task Goal Orientation	.009	.077	.121	.904
Need for Cognition	.240	.222	1.082	.282
Prior Knowledge	.079	.080	.988	.326
Multiple R^2: .057		Adjusted R^2: -.027		
$F(9, 101) = .684$, $p = .721$				

Table 8

Linear Regression Model Predicting Perceived Essay Answer Accuracy

Variable	Estimate	Standard Error	T Value	P-Value
Intercept	4.517	1.746	2.587	.011
Searches (Perform-Search)	.006	.070	.088	.930
Search Links (View-Search-Link)	-.003	.014	-.218	.828
Terms (View-Term)	.049	.067	.731	.466
Term Links (View-Term-Link)	-.006	.011	-.546	.586
Ability-Approach Orientation	-.026	.166	-.156	.877
Ability-Avoid Goal Orientation	-.080	.132	-.605	.546
Task Goal Orientation	.071	.134	.532	.596
Need for Cognition	-.218	.386	-.565	.573
Prior Knowledge	.200	.138	1.443	.152
Multiple R^2: .045		Adjusted R^2: -.040		
$F(9, 101) = .524$, $p = .854$				

Table 9

Linear Regression Model Predicting Perceived Essay Answer Validity

Variable	Estimate	Standard Error	T Value	P-Value
Intercept	4.392	1.777	2.471	.015
Searches (Perform-Search)	-.015	.071	-.203	.840
Search Links (View-Search-Link)	.017	.015	1.153	.251
Terms (View-Term)	.0116	.068	1.707	.091
Term Links (View-Term-Link)	-.024	.011	-2.238	.027
Ability-Approach Orientation	-.106	.169	-.628	.532
Ability-Avoid Goal Orientation	.039	.134	.294	.769
Task Goal Orientation	.052	.137	.378	.706
Need for Cognition	-.321	.392	-.817	.416
Prior Knowledge	.119	.141	.846	.400
Multiple R^2: .072		Adjusted R^2: -.010		
$F(9, 101) = .877$, $p = .549$				

4.2. Discussion

Using the methodology described, we investigated whether the behavior and performance of the users was impacted by individual differences. In addition, we sought to identify any strategies employed by the users as they completed the essay task assigned to them. Finally, we aimed to determine whether there was any relation between performance, behavior, and self-assessment.

Research Question 1. Based on the traces of data collected following student use of both concept maps and search tools to complete an essay writing task, can meaningful learning strategies be identified and if so, what are their characteristics?

In order to examine whether participants exhibited a preference for the search tool over the concept map (hypothesis 1), we began with a statistical analysis of the actions performed by participants (Table 3). We found that participants made use of the concept map significantly more than they made use of the search tool. On average, participants viewed 12 concept map terms and performed 6.68 searches, while viewing an average of 47.60 websites from the concept map and an average of 20 websites from the searches they performed. This indicates that participants exhibited a preference for using the concept map over the search tool. One possible explanation for this result is the concept of novelty in learning, wherein learners are motivated by novelty when presented with multiple learning technologies [Gillett-Swan 2017; Moreillon 2015]. Another explanation for this might be the perceived speed of using the concept map. Rather than having to type out queries in the text-based search tool, users can click directly on items the concept map, which effectively works as though users are performing searches for the contents of the concept map. This result is supported by research into the use of information visualization techniques to present graphical search results, which has shown that visual representation of concepts can provide users with context that allows them to navigate through topics with greater speed [Carter-Templeton 2016; Shneiderman 2007].

Our second prediction was that there would be observable patterns in the behavior of the participants as they research the topic that is provided to them (hypothesis 2). In completing our analysis, we observed three patterns of behavior.

First, the plot of actions used during the essay writing task (Figure 12) show that every participant made use of both the concept map and search tools at least once. This represents a pattern of behavior on the part of the learners to at least try both tools at least once. This observation is consistent with research into self-directed, distance-based learning, which has shown that when learners are presented with different of information, they will explore them in order to identify which one best meets their needs [Belanger 1999; Moreillon 2015], as well as other research which has shown learners will often pursue a deliberate strategy of taking advantage of all of the tools available to them [Belanger 1999].

Second, the hierarchical clustering analysis (Figure 14) and representative sequence plot (Figure 15) revealed two distinct clusters, representing a class of behavior. The High Engagement Group completed the assigned task by performing relatively long event sequences, while the Low Engagement group complete the task by performing relatively short event sequences.

Third, the overall behavior of all participants followed a similar pattern of navigation. Learners started off in the concept map with a View-Term action, followed by a pattern of alternating between the View-Term and View-Term-Link actions, and then, towards the end of the event sequence, concluded their activities with a sequence of Perform-Search and View-Search-Link actions. At a high level, all the learners started their exploration using the concept map, and then after a period of time move on to exploring the topic through the search tool. This type of behavior, when a learner switches tactics, tools, or behaviors, has been observed in previous studies, particularly when the learning materials are highly domain-specific and outside the realm of familiarity for the learner [Butcher 2011; Kules 2008]. This change in tactic has been observed when the learner believes they have extracted all the value they can from the first resource and are moving on to a second resource [Rovers 2018]. In other words, the learner believes they have learned everything they can from the concept map and are now turning to the search tool in order to perform specific targeted searches. The learners are effectively moving from a *navigation* strategy (navigating through related materials) to a *selection* strategy (performing queries and browsing through the results), as described in self-directed learning research [Chi 2009; Marchionini 2006]. In the context of our study, this corresponds to the learners using the concept map to cover the topic at a high level, and then performing searches to find specific targeted information.

Research Question 2. Are the identified learning strategies associated with any post-study outcomes including essay scores?

We predicted a correlation between the strategy participants employ researching the topic and exploring the concept map, and the essay scores (hypothesis 3). In answering RQ1, we identified three patterns. The first pattern of behavior, in which learners using both the concept map and search tools, was observed across all learners. Similarly, the third pattern of behavior, wherein learners started with a *navigation* strategy, and then transitioned to a *selection* strategy, was consistent across all learners. As such, these two patterns of behavior covered all possible learning outcomes, and were not associated with a specific learning outcome.

However, the second pattern we identified, in which learners spent a variable amount of time completing the task, was not uniform across all learners. Based on our analysis of the event sequences, learners were clustered into two distinct groups based on the relative amount of time spent completing the essay writing task (Figures 14 and 15). The High Engagement group spent significantly longer time completing the assigned task (MSeconds = 3670.07, SD = 613.61) compared to the Low Engagement group (MSeconds = 859.44, SD = 246.44). The Low Engagement group averaged 859.44 seconds to complete the assigned task. In contrast to this, the High Engagement group spent, on average, more than three times the Low Engagement group completing the task. Further analysis of the groups showed that the High Engagement Group achieved significantly higher average essay marks (M = 8.89, SD = 1.54) compared to the Low Engagement Group (M = 3.80, SD = 2.37). This indicates a positive correlation between the amount of time completing the task (time-on-task), and the essay score achieved.

Comparisons between the two groups on the four post-study variables (perceived usefulness of the concept map, perceived usefulness of search tool, perceived essay task accuracy, and perceived essay task validity) showed the Low Engagement group to have a significantly higher score for perceived usefulness of the concept map than the High Engagement group, with no other significant differences between the two groups. While there was no difference in actual usage of the concept map between the High and Low Engagement groups, the perceived usefulness scores for the Low Engagement group might reflect on the tendency for learners within this group to minimize time spent on task. This is consistent with research findings into information visualization tools [Carter-Templeton 2016; Shneiderman 2007] and might also indicate an overall preference for the navigation learning strategy over the selection learning strategy amongst learners that fall into the Low Engagement group. Conversely, the High Engagement group, which exhibited a tendency to spend significantly greater time on task relative to the Low Engagement group, was less motivated by time-saving tools. The positive correlation between the amount of time completing the task, and the essay score achieved reflects a choice to prioritize for accuracy and correctness over time on task.

The third pattern we observed, in which learners followed a similar pattern of navigation through the learning materials, was uniform across all learners, and was thus not associated with any specific learning outcome.

Research Question 3. Are individual differences associated with final measured outcomes?

Based on prior research, we expected to see a relationship between motivation, prior knowledge, and final measured outcomes. We predicted a correlation between the relative level of motivation and the amount of time the participant spent completing the study (hypothesis 4), as well as a negative correlation between prior knowledge and the amount of time the participant spent completing the task (hypothesis 5). In answering RQ2, we found a positive correlation between the amount of time completing the task (time-on-task) and the essay score achieved, as well as a positive correlation between perceived prior knowledge and time-on-task. Given this correlation, and prior research which has shown a relationship between individual differences and effort [DeCaro 2012; Wolters 2004], we expected our analysis would show a connection between motivation, effort (time), and learning outcomes.

However, we found no correlation between any other individual differences and final measured outcomes. Regression analysis of the four dependent variables with all nine predictor variables found no other correlation, with F-statistics smaller than 1, all p-values exceeding .05, and adjusted R2 values approximately equal to 0 (Tables 6 to 9). These findings from the regression analysis aligns with the findings shown in the correlation matrix (Table 18 and 19), as discussed in our Analysis for RQ1. However, in answering RQ1 and RQ2, there is a weak indirect relationship in that perceived prior knowledge correlated to time-on-task and then time-on-task was correlated with essay score (Table 18 and 19).

4.3. Implications

In our study we found three observable patterns of behavior in the learners' activities, while completing the self-directed learning activity. For those learners with low perceived prior knowledge, the strategies attempted to minimize the amount of time spent on task (Time-On-Task), while for those with higher perceived prior knowledge, the strategies attempted to ensure the learner answered the essay questions as completely and as correctly as possible. Further, we found correlation between the amount of time spent on task and the learning outcomes. As a methodological implication, this indicates that there would potentially be value in structuring self-directed learning differently depending on perceived prior knowledge. Providing different tools, materials, or instructional information to different learners depending on their self-assessed prior knowledge could lead to improved learning outcomes, and a more evenly distributed investment of time from all learners. The relationship we found between effort and learning outcome, while reinforcing other research, has no broader implications when taken on its own, and seen outside the context of the implications with perceived prior knowledge.

While we did find that learners exhibited a preference for using the concept map tool, we were unable to find a correlation showing any benefit to using the concept map over the search tool in the context of the essay writing task given to the learners.

4.4. Limitations and Future Work

Although we did not find correlation between the concept map usage and the quality of the work completed by the learner, it’s important to note that the structure of our study was not completely open-ended. The participants were provided with a basic guide taking them through the concept map and search tools. The instructions needed to be ordered in some way, and so participants were arbitrarily shown the concept map first, followed by the search tool. The guided nature of the instructions may have inadvertently introduced some bias. A future study may wish to control for this by randomly dividing participants into two groups, and then varying the order of the instructions for each group, in order to control for and study any differences in behavior or performance. In addition, although we examined the perceived usefulness of the concept map and search tool, we did not examine the perceived effectiveness of the instructions provided to the participants. It is possible that some participants did not fully understand how to use one or more of the tools, which may in turn have impacted their overall behavior and performance in the study.

In this study, we considered the impact of individual differences using Achievement Goal Orientation and Prior Knowledge Assessment. However, it is important to note that Achievement Goal Orientation is a tool based on a theory that continues to undergo change and development. As the Achievement Goal Orientation theory and tool changes over time, so too does our understanding and application need to change as well. Due to the timing of our study, the latest updates to the Achievement Goal Orientation instrument were not yet available. Future studies along similar lines would want to consider making use of the latest available tools and techniques.

4.5. Conclusions

The goal of our study was to investigate the effects of individual differences and information visualization on exploratory search in a self-directed learning task. Specifically, we sought to examine learning behaviors relative to the use of the concept map and search tools in order to assess for any correlations between behavior and learning outcomes, controlling for individual differences and prior knowledge.

We predicted a correlation between the use of the concept map and the learning outcomes. While we were unable to find correlations between the use of the concept map tool and the learning outcomes in the assigned essay writing task, we did find a positive correlation between perceived prior knowledge and the amount of time spent completing the task (time-on-task), as well as a positive correlation between the amount of time completing the task, and the essay score achieved. These findings align with other research into self-directed learning.

We predicted that the learners would follow observable patterns of behavior, and we were able to identify three patterns of behavior. These patterns constituted strategies used by the learners to their task. One of the patterns, in which users were classified by the relative amount of time on task, found strong positive correlation to perceived prior knowledge, and the learning outcomes. We also identified strategies related to the learners use of tools. First, all participants made use of both learning tools, and second, all learners started with the concept map tool before transitioning to the search tool. These two strategies correspond to a pattern of behavior in which the learners transitioned from the navigation self-directed learning strategy to selection self-directed learning strategy. While there was no specific correlation, as these strategies were found in all participants, the observation of this behavior was not predicted based on prior research.

We expected to see a positive relationship between learner behaviors that focused on making use of the concept map tool and the learner outcomes, with higher essay scores correlating to increased usage of the concept map tool. However, although we observed overall higher usage of the concept map tool compared to usage of the search tool, we did not observe any correlation between use of the concept map tool and improved performance at the assigned exploratory learning task (i.e. completing the essay), or between high usage of the concept map tool and high perceived usefulness scores. The increased usage of the concept map tool over the search tool might indicate that learners saw some benefit to using the concept map tool compared to the search tool. However, the increased usage did not correlate to the perceived usefulness scores, or to the essay scores. Other studies that have examined the effectiveness of using various tools, including concept maps, to perform and navigate through web searches have noted that users have tended to both favor and achieve better results using web search and navigation tools they are familiar with [Cañas 2005; Carvalho 2001; Leake 2004; Sebrechts 1999]. Search engines are not only a familiar and widely accepted technology, but they have been proven to be very effective at finding the specific results that users are looking for when they perform detailed keyword-based search queries [Gordon 1999; Jansen 2006; Lewandowski 2015; Wilson 2010]. It is reasonable to conclude that, given a choice between tools, the users in our study would not differ significantly from users in other studies in their preference for familiar tools that they are already experienced with and comfortable using.

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Appendix A: Ethics Review Approvals

The Northern Alberta Institute of Technology
Research Ethics Board
Certificate of Ethics Approval for Research Proposal

Principal Investigator: Nathan Laan

Co-Investigator(s): n/a

Organization(s): Athabasca University (Approved March 11, 2016: File No: 22143)

Project Title: Effects of Individual Differences and Visual Information Seeking on Learning Strategies in Essay Writing

Grant/Contract Agency: none

Research Ethics Application #: 2016-03

Research Ethics Approval **Expiry** Date: March 24, 2017

Certification of the Northern Alberta Institute of Technology
Research Ethics Approval

I have received your application for research ethics review and conclude that your proposed research meets the Northern Alberta Institute of Technology Policy for research involving human subjects (IR 10.0). On behalf of the Northern Alberta Institute of Technology's Research Ethics Board (NAIT REB), I am providing research ethics approval for your proposed project.

This research ethics approval is valid for one year. To request a renewals after (today's date + 1 year) please contact me and explain the circumstances, making reference to the research ethics review number assigned to this projects (see above). Also, if there are significant changes to the project that need to be reviewed, or if any adverse effects to human participants are encountered in your research, please contact REB@nait.ca immediately.

Chair, Research Ethics Board

The Kings University College
Research Ethics Board
Certificate of Ethics Approval for Research Proposal

Hi Nathan,

Your project has been approved by the King's REB. We wish you all the best with your research and will look forward to hearing from you when your work has been completed.

Chair, King's Research Ethics Board

The King's University
9125 - 50 Street, Edmonton, AB T6B 2H3
P 780.465.3500 EXT 8045
KINGSU.CA

Athabasca University
RESEARCH CENTRE

March 11, 2016

Mr. Nathan Laan
Faculty of Science & Technology\School of Computing & Information Systems
Athabasca University

File No: 22143

Expiry Date: March 10, 2017

Dear Nathan Laan,

The School of Computing and Information Systems Departmental Ethics Review Committee, acting under authority of the Athabasca University Research Ethics Board to provide an expedited process of review for minimal risk student researcher projects, has reviewed you project, 'Effects of Individual Differences and Visual Information Seeking on Learning Strategies in Essay Writing'.

Your application has been **Approved on ethical grounds** and this memorandum constitutes a ***Certification of Ethics Approval***. It is noted that ethics approval must still be granted at Northern Alberta Institute of Technology and King's University. *No participant recruitment or data collection can proceed until these further ethical approvals are provided.* Please email the approvals to rebsec@athabascau.ca when they are received.

AUREB approval, dated March 11, 2016, is valid for one year less a day.

As you progress with the research, all requests for changes or modifications, ethics approval renewals and serious adverse event reports must be reported to the Athabasca University Research Ethics Board via the Research Portal.

To continue your proposed research beyond March 10, 2017, you must apply for renewal by completing and submitting an Ethics Renewal Request form. Failure to apply for **annual renewal** before the expiry date of the current certification of ethics approval may result in the discontinuation of the ethics approval and formal closure of the REB ethics file. Reactivation of the project will normally require a new Application for Ethical Approval and internal and external funding administrators in the Office of Research Services will be advised that ethical approval has expired and the REB file closed.

When your research is concluded, you must submit a Project Completion (Final) Report to close out REB approval monitoring efforts. Failure to submit the required final report may mean that a future application for ethical approval will not be reviewed by the Research Ethics Board until such time as the outstanding reporting has been submitted.

At any time, you can login to the Research Portal to monitor the workflow status of your application.

If you encounter any issues when working in the Research Portal, please contact the system administrator at research_portal@athabascau.ca.

If you have any questions about the REB review & approval process, please contact the AUREB Office at (780) 675-6718 or rebsec@athabascau.ca.

Sincerely,

Chair, School of Computing and Information Systems Departmental Ethics Review Committee
Athabasca University Research Ethics Board

Athabasca University
RESEARCH CENTRE

CERTIFICATION OF ETHICAL APPROVAL - RENEWAL

The Athabasca University Research Ethics Board (AUREB) has reviewed and approved the research project noted below. The AUREB is constituted and operates in accordance with the current version of the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS) and Athabasca University Policy and Procedures.

Ethics File No.: **22143**

Principal Investigator:
Mr. Nathan Laan, Graduate Student
Faculty of Science & Technology\School of Computing & Information Systems

Supervisor:
Dr. Dunwei Wen (Supervisor)

Project Title:
Effects of Individual Differences and Visual Information Seeking on Learning Strategies in Essay Writing

Effective Date: February 12, 2018 **Expiry Date**: February 12, 2019

Restrictions:

Any modification or amendment to the approved research must be submitted to the AUREB for approval.

Ethical approval is valid *for a period of one year*. An annual request for renewal must be submitted and approved by the above expiry date if a project is ongoing beyond one year.

A Project Completion (Final) Report must be submitted when the research is complete *(i.e. all participant contact and data collection is concluded, no follow-up with participants is anticipated and findings have been made available/provided to participants (if applicable))* or the research is terminated.

Approved by: **Date:** February 12, 2018

Athabasca University Research Ethics Board

Athabasca University Research Ethics Board
University Research Services, Research Centre
1 University Drive, Athabasca AB Canada T9S 3A3
E-mail rebsec@athabascau.ca
Telephone: 780.675.6718

Appendix B: Questionnaires

Table 10

Pre-test Achievement Goal Orientation (AGO) Questionnaire

Group	#	Question
AGOG1 (Ability Approach Orientation)	1	It is important to me to do better than other participants in this study.
	2	My goal is to get better search results than most of the other participants in this study.
	3	I am striving to demonstrate my ability relative to others participants in this study.
	4	I am motivated by the thought of outperforming others participants in this study.
	5	It is important to me to do well compared to other participants in this study.
	6	I want to do well in this task to show my ability to my family, friends, advisors, or others.
AGOG2 (Ability Avoid Goal Orientation)	7	I am thinking to myself, "What if I do badly in this task?”
	8	I worry about the possibility of getting bad results in this task.
	9	My fear of performing poorly is often what motivates me.
	10	I just want to avoid doing poorly.
	11	I'm afraid that if I ask researchers involved in this study a "dumb question", they might not think I'm very smart.
	12	My goal for this task is to avoid performing poorly.
AGOG3 (Task Goal Orientation)	13	I want to learn as much as possible while completing this task.
	14	It is important for me to understand the content that I am being asked to study in this experiment as thoroughly as possible.
	15	I hope to have gained knowledge when I am done with this task.
	16	I desire to completely master the material presented in this task.
	17	When presented with situations where I might learn new things, I prefer material that arouses my curiosity, even if it is difficult to learn.
	18	When presented with situations where I might learn new things, I prefer material that really challenges me so I can learn new things.

Table 11

Pre-test Need for Cognition (NFC) Questionnaire

Group	#	Question
NFCG1	1	I prefer complex to simple problems
	2	I like to have the responsibility of handling a situation that requires a lot of thinking
	3	Thinking is not my idea of fun
	4	I would rather do something that requires little thought than something that is sure to challenge my thinking abilities
	5	I try to anticipate and avoid situations where there is a likely chance I will have to think in depth about something
	6	I find satisfaction in deliberating hard and for long hours
NFCG2	7	I only think as hard as I have to
	8	I prefer to think about small, daily projects than long-term ones
	9	I like tasks that require little thought once I've learned them
	10	The idea of relying on thought to make my way to the top appeals to me
	11	I really enjoy a task that involves coming up with new solutions to problems
	12	Learning new ways to think doesn't excite me very much
	13	I prefer my life to be filled with puzzles that I must solve
NFCG3	14	The notion of thinking abstractly is appealing to me
	15	I prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought
	16	I feel relief rather than satisfaction after completing a task that required a lot of mental effort
	17	It's enough for me that something gets the job done; I don't care how or why it works
	18	I usually end up deliberating about issues even when they do not affect me personally

Table 12

Pre-Test Prior Knowledge Assessment Questionnaire

Group	#	Question
PKAG1	1	Would you say you are knowledgeable about computer technology?
	2	Would you say you are knowledgeable about technology in general?
PKAG2	3	Would you say you are knowledgeable about the internet in general?
	4	Would you say you are knowledgeable about web search engines?
PKAG3	5	Would you say you are knowledgeable about security technology?
	6	Would you say you are knowledgeable about any specific security technologies?

Table 13

Post-Test Concept Map Perceived Usefulness Questionnaire

#	Question
1	My task would have been difficult to perform without the concept map
2	Using the concept map saved me time
3	Using the concept map allowed me to accomplish more work than would otherwise be possible
4	Using the concept map enhanced my effectiveness on the task
5	Using the concept map improved the quality of the work I do
6	Overall, I found the concept map useful in my task
7	Overall, the results I found using the concept map were accurate

Table 14

Post-Test Search Tool Perceived Usefulness Questionnaire

#	Question
1	My task would have been difficult to perform without the search tool
2	Using the search tool saved me time
3	Using the search tool allowed me to accomplish more work than would otherwise be possible
4	Using the search tool enhanced my effectiveness on the task
5	Using the search tool improved the quality of the work I do
6	Overall, I found the concept map useful in my task
7	Overall, the results I found using the search tool were accurate

Table 15

Post-Test Self Evaluation Questionnaire

#	Question
1	The answer I provided for question 1 (the definition of a security exploit) was accurate
2	The answer I provided for question 2 (example of a security exploit) was valid

Appendix C: Analysis

Table 16

Transition Matrix for the High Engagement Group

From	To			
	Perform-Search	View-Search-Link	View-Term	View-Term-Link
Perform-Search	.195	.786	.020	.000
View-Search-Link	.000	1.00	.000	.000
View-Term	.000	.000	.000	1.00
View-Term-Link	.014	.000	.176	.810

Table 17

Transition Matrix for the Low Engagement Group

From	To			
	Perform-Search	View-Search-Link	View-Term	View-Term-Link
Perform-Search	.130	.852	.018	.000
View-Search-Link	.451	.486	.063	.000
View-Term	.000	.000	.000	1.00
View-Term-Link	.035	.000	.296	.669

Table 18

Correlation Matrix

	Essay Score	Searches	Search Links	Terms	Term Links	Time-On-Task	AGOG1	AGOG2	AGOG3	NFC	PKA	PUST	PUTN
Essay Score	1	0.3457	0.6933	0.6121	0.7019	0.9266	0.8514	0.8543	0.8476	0.0386	0.8650	-0.0815	0.1846
Searches	0.3457	1	0.7529	0.3870	0.4700	0.3532	0.2496	0.2447	0.2235	-0.0653	0.2986	-0.1622	0.1132
Search Links	0.6933	0.7529	1	0.6815	0.8208	0.6684	0.5468	0.5498	0.5631	-0.0603	0.5990	-0.1104	0.1909
Terms	0.6121	0.3870	0.6815	1	0.9324	0.6261	0.4967	0.5712	0.4768	-0.0054	0.5620	-0.0726	0.1659
Term Links	0.7019	0.4700	0.8208	0.9324	1	0.7102	0.5668	0.6193	0.5754	-0.0521	0.6183	-0.1042	0.1858
Time-On-Task	0.9266	0.3532	0.6684	0.6261	0.7102	1	0.8636	0.8603	0.8674	-0.0201	0.7669	-0.0935	0.2490
AGOG1	0.8514	0.2496	0.5468	0.4967	0.5668	0.8636	1	0.8725	0.8865	-0.0318	0.6864	-0.0992	0.2113
AGOG2	0.8543	0.2447	0.5498	0.5712	0.6193	0.8603	0.8725	1	0.8589	0.0302	0.7380	-0.0547	0.2604
AGOG3	0.8476	0.2235	0.5631	0.4768	0.5754	0.8674	0.8865	0.8589	1	0.0696	0.7361	-0.1014	0.2181
NFC	0.0386	-0.0653	-0.0603	-0.0054	-0.0521	-0.0201	-0.0318	0.0302	0.0696	1	0.1404	0.0697	-0.0909
PKA	0.8650	0.2986	0.5990	0.5620	0.6183	0.7669	0.6864	0.7380	0.7361	0.1404	1	-0.0945	0.1479
PUST	-0.0815	-0.1622	-0.1104	-0.0726	-0.1042	-0.0935	-0.0992	-0.0547	-0.1014	0.0697	-0.0945	1	-0.0373
PUTN	0.1846	0.1132	0.1909	0.1659	0.1858	0.2490	0.2113	0.2604	0.2181	-0.0909	0.1479	-0.0373	1

Table 19

Correlation Matrix P-values

	Essay Score	Searches	Search Links	Terms	Term Links	Time-On-Task	AGOG1	AGOG2	AGOG3	NFC	PKA	PUST	PUTN
Essay Score	NA	0.8824	0.7215	0.8323	0.9193	0.0144	0.9320	0.9575	0.9615	0.6326	0.0775	0.7146	0.8984
Searches	0.8824	NA	0.9048	0.6702	0.7445	0.9303	0.4901	0.9367	0.9270	0.7714	0.2565	0.0917	0.0847
Search Links	0.7215	0.9048	NA	0.3586	0.1921	0.4378	0.7070	0.4710	0.5788	0.9923	0.2775	0.4630	0.5065
Terms	0.8323	0.6702	0.3586	NA	0.5962	0.5747	0.6660	0.0795	0.5988	0.7671	0.8045	0.5218	0.4397
Term Links	0.9193	0.7445	0.1921	0.5962	NA	0.7393	0.2390	0.3866	0.4683	0.1938	0.3553	0.6023	0.0679
Time-On-Task	0.0144	0.9303	0.4378	0.5747	0.7393	NA	0.6392	0.9282	0.5970	0.5094	0.0376	0.7506	0.5045
AGOG1	0.9320	0.4901	0.7070	0.6660	0.2390	0.6392	NA	0.9128	0.5470	0.8239	0.3459	0.4723	0.7161
AGOG2	0.9575	0.9367	0.4710	0.0795	0.3866	0.9282	0.9128	NA	0.7870	0.3252	0.9903	0.2372	0.2752
AGOG3	0.9615	0.9270	0.5788	0.5988	0.4683	0.5970	0.5470	0.7870	NA	0.1680	0.3713	0.8404	0.4670
NFC	0.6326	0.7714	0.9923	0.7671	0.1938	0.5094	0.8239	0.3252	0.1680	NA	0.1866	0.2993	0.9687
PKA	0.0775	0.2565	0.2775	0.8045	0.3553	0.0376	0.3459	0.9903	0.3713	0.1866	NA	0.1600	0.9229
PUST	0.7146	0.0917	0.4630	0.5218	0.6023	0.7506	0.4723	0.2372	0.8404	0.2993	0.1600	NA	0.7105
PUTN	0.8984	0.0847	0.5065	0.4397	0.0679	0.5045	0.7161	0.2752	0.4670	0.9687	0.9229	0.7105	NA