Exploring Student Information Problem Solving Behaviour Using Fine-Grained Concept Map and Search Tool Data

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Abstract

For learners to be successful in an information problem solving task, they should be able to effectively regulate their own behaviour. Despite views that such behaviour may come naturally to an individual, research generally shows that some learners do experience problems with information problem solving that may stem from such things

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as limited prior knowledge. As a means of addressing this challenge, the authors explored how the provision of both a concept map and search tool could overcome barriers to effective information problem solving. This was explored in the current study using data collected from 111 undergraduate students who completed an information problem solving activity, wherein a concept map and search tool were provided to help them write two short essays. Through the use of event-sequence analysis and hierarchical clustering, two information problem solving strategy groups were identified (High Engagement and Low Engagement), which differed across time-on-task and essay grades. Additional analyses were undertaken to explore self-reported prior knowledge or motivation as predictors of group assignment. The findings show that even when presented with opportunities (i.e., concept map) to support effective information problem solving, not all learners will take advantage or glean the benefits of such tools. Trace data methodology is shown to be a promising approach to explore information problem solving behaviour that can overcome the limitations of solely relying upon self-report measures.

1   Introduction

Information problem solving encompasses those challenges in which an individual is required to identify, examine, and communicate information for the purposes of creating a product (Winne, Vytasek, et al., 2017). In a sense, information problem solving involves the use of both strategies and skills (cognitive and metacognitive; Brand-Gruwel, Wopereis, & Vermetten, 2005), all of which need to be fleshed out for the purposes of providing actionable feedback to relevant stakeholders (e.g., learners and learning designers; Brand-Gruwel, Wopereis, & Walraven, 2009). Without undertaking appropriate research to explore this decomposition of the processes involved in information problem solving tasks, there is no evidential basis for creating recommendations directed at improving information problem solving skills (Winne, Nesbit, & Popowich, 2017). This is particularly in light of work showing that learners may engage in ineffective information problem solving strategies within web-based environments (Raes, Schellens, & Wever, 2010) or hold inaccurate beliefs about their skill set (Gross & Latham, 2012). Examples of ineffective information problem solving include not being able to effectively evaluate information or conducting advanced searches (e.g., using

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Boolean operators; Ivanitskaya, O'Boyle, & Casey, 2006; Judd & Kennedy, 2011). Put differently, learners have issues associated with metacognitive monitoring and control during information problem solving tasks. For example, the inability to conduct advanced searches demonstrates weaknesses in monitoring how to correctly construct a query and select the relevant operators that would narrow the search space (Winne, 2011). Interventions to remedy these limitations are a possibility, but with research that has had a limited focus on at-risk students and an over-reliance on self-reported data, any developments could be questioned.

A typical example of self-reports being used in information problem solving research would be to regress academic performance onto an array of previously measured self-regulated learning factors (Harding et al., 2019). Although this approach may identify possible patterns in behaviour that could be attributable to grade attainment, it nevertheless conveys insufficient detail about the information problem solving process (Winne, Nesbit, & Popowich, 2017). An alternative, and more insightful approach, should instead be adopted, wherein researchers take advantage of those learning environments through which granular data about a learner can be obtained (Winne, Nesbit, & Popowich, 2017; Gašević, Dawson, & Siemens, 2015; Winne, 2006). Through this method of gathering fine-grained data, the researchers can then obtain a clearer image of how learners engage in a variety of information problem solving strategies as they work towards completing information problems. The current work seeks to investigate the utility of granular data as a way of exploring how learners complete an information problem solving task, specifically when using both a concept map and keyword-based search tool.

1.1   Information Problem Solving Model

Metacognitive models of information problem solving have been identified by Lazonder and Rouet (2008) as an important directive due to how integral metacognitive skills are to success in information problem solving tasks. Winne, Vytasek, et al. (2017) posit one such model of information problem solving, which is interwoven with their model of self-regulated learning (Winne & Hadwin, 1998). Central to this model is the recognition of a learner being an agent of their own learning (Winne, 2006), wherein they autonomously select and synthesise information from various sources so that they can meet their set goals. During this process, the learner is metacog-

nitively monitoring whether the information gathered aligns with the overarching goal such as providing a relevant answer to an essay question. On the basis of this monitoring, the learner may then change their strategies accordingly. Alternate to the model of Winne, Vytasek, et al. is the internet model of information problem solving proposed by Brand-Gruwel et al. (2009). Brand-Gruwel et al. outline five sequentially ordered skills (define information problem, solve information, scan information, process information, and organise and present information) that are required when the internet is used to solve an information problem (Walraven, Brand-gruwel, & Boshuizen, 2008). With the enactment of each skill, the learner is engaging in regulation activities to evaluate whether the adopted approach will lead to set goals being met, akin to the model of Winne, Vytasek, et al..

In the context of information problem solving, the aforementioned models of Winne, Vytasek, et al. and Brand-Gruwel et al. state that the initial step taken by a learner is to set a goal; conditions that are both internal and external to the learner are important factors here. Internal conditions may encompass levels of prior knowledge or motivation, and can be used to explain differences in performance of information problem tasks across groups. For example, White, Dumais, and Teevan (2009) and Brand-Gruwel et al. (2005) found domain and information problem solving experts to spend a longer amount of time on a task compared to non-experts, respectively. External conditions, on the other hand, refer to aspects of the environment such as instructional cues or task support (Frerejean, van Strien, Kirschner, & Brand-Gruwel, 2016). In the research undertaken by Wopereis, Brand-Gruwel, and Vermetten (2008), learners were provided with training on aimed at improving information problem solving skills such as how to seek information. Compared to a group not receiving such training, Wopereis et al. found learners who had training to spend more time reading information. Together, the aforementioned points seek to illustrate that the interplay of internal and external conditions will be associated with how the learner engages with an array of tools to search, highlight, annotate, and bookmark various information. Applications of these operations can then allow the learner to create products such as writing an essay, which can then be evaluated and revised.

Assuming that all learners will successfully self-regulate their learning or information problem solve is not, however, an appropriate generalisation. In a review undertaken by Walraven et al. (2008), it was found that, irrespective of age group, individuals experienced problems in their information problem solving strategies such as regulating their behaviour and judging identified in-

formation (Ivanitskaya et al., 2006; Judd & Kennedy, 2011; Raes et al., 2010). For interventions to be devised that could address such information problem solving deficiencies, there is a need to better understand the strategies that are adopted and enacted within such situations. Identification and formulation of typologies for information problem solving strategies are therefore an important direction for research. Approaches to understanding information problem solving behaviour that predominately utilise self-report measures (Puteh & Ibrahim, 2010) such as the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & Mckeachie, 1993) are limited due to the construct being represented as an aptitude (Winne & Perry, 2000). What is meant by this is that items are framed so that respondents provide a general perception of their behaviour over many contexts, in contrast to a singular learning event. Winne and Perry posits that event based representations of learning can instead be obtained through the application of trace methodologies, as actions (e.g., navigation of a concept map) are collected. In doing so, researchers are provided with data showing how information problem solving strategies unfold over the course of an information problem solving activity; incorporation of self-report measures can address gaps in trace data (e.g., attitudes towards information problem solving strategies can be captured).

The premise of this work is to therefore leverage both trace and self-report methodologies to describe the processes and strategies enacted during a information problem solving activity (Gašević et al., 2015; Winne, 2006; Winne, Nesbit, & Popowich, 2017); thereby drawing on the advantages of both approaches. As discussed previously, trace methodologies allow the exploration of information problem solving behaviour in an unobtrusive manner (Winne & Perry, 2000). Still this needs to be balanced with the issues of construct validity in big data settings (Braun & Kuljanin, 2015) and the issue of coding agreement (Winne & Perry, 2000). Frameworks are offered (Saint, Gašević, & Pardo, 2018; Siadaty, Gašević, & Hatala, 2016), but they are inconsistently applied and appropriate methods of validation have yet been agreed upon. Expecting respondents to complete self-report measures at multiple times within a short time span may be inappropriate due to fatigue. Irrespective of this limitation, self-report measures have been subject to validation techniques and can provide insights that are not attainable from trace methodologies (e.g., motivations, self-efficacy, and attitudes). While both approaches (trace methodologies and self-reports) do have their limitations, they also have advantages that are mutually beneficial (i.e., behavioural

traces can be captured alongside variables that are not observable). Thus, the anticipated outcome of having these two data streams would then be to better identify and characterise enacted strategies of students. On the basis of this groundwork, researchers can begin to explore how it can be leveraged to better understand enacted strategies and devise ways to create actionable interventions (Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2019; Winne, 2019).

1.2 Conditions and Information Problem Solving

As outlined above, tasks definitions, goals set, and strategies enacted are influenced by an integration of internal and external conditions (Winne & Hadwin, 1998; Winne, 2010). Internal conditions span such things as self-efficacy beliefs and task knowledge, all of which can affect self-regulatory behaviours (Zimmerman, 2000). External conditions, on the other hand, refer to the resources available, instructional cues, and the time-on-task that is permitted. For the current work, both internal and external conditions are considered as variables associated with information problem solving behaviour, discussion of each follows.

1.2.1 Internal Conditions and Information Problem Solving

Internal conditions can be thought as all encompassing with regards to the number of variables that could conceivably fall under this terminology. For the purposes of this research, focus was placed upon three constructs: need for cognition, achievement goal orientation, and prior knowledge. These were selected on the basis of the identified associations they have with processes involved in information problem solving (Cazan & Indreica, 2014; Grass et al., 2019; Moos & Azevedo, 2008; Pintrich, Zusho, Schiefele, & Pekrun, 2001). An additional reason behind the selection of internal conditions was to explore how such measures provide information that is not obtainable from traces (e.g., logs will not provide subjective measures of how learners perceive their knowledge about a topic to be). Integration of data captured from tools designed to support information problem solving with those obtained from questionnaires should therefore provide a more complete picture of learner behaviour.

Learners tendency to engage in and enjoy information problem solving activities are believed to be encapsulated by what is referred to as need

for cognition (Cacioppo, Petty, & Feng Kao, 1984). Through the use of path-modelling, researchers have shown need for cognition to be positively associated with the use of information problem solving strategies (Cazan & Indreica, 2014). According to Cazan and Indreica, this finding is indicative of a higher need for cognition being associated with critically processing and relating information. In an information problem solving situation, the ability to appraise different information in a critical manner is fundamental, as is being able to integrate different forms of information. On this basis, the inclusion of need for cognition as a measure of an associated internal condition was considered to be a useful factor.

Achievement motivations are an important factor in how learners approach particular tasks, particularly in relation to knowing whether a learner is oriented towards task mastery or displaying competence (Elliot, Murayama, & Pekrun, 2011). These orientations can further be deconstructed into whether the individual chooses to undertake the activity with a view of avoiding failure or to seek success. With regards to how goal orientation affect self-regulatory behaviour, Pintrich et al. (2001) have found learners who are motivated to master a task are more likely to set goals, monitor progress, and change strategies (Lin, 2019). Performance orientations, on the other hand, lead to inconsistent learner patterns with a lower likelihood of engaging in a regulation of their behaviour. Within the context of information problem solving tasks, it is reasonable to assume that the strategies enacted by learners may be affected by their overall goal orientations. This would relate, in particular, to how much time is dedicated to searching for various information to complete the task at hand.

Prior knowledge is an important determinant in information problem solving activities (Chen & Macredie, 2010; Minetou, Chen, & Liu, 2008). As found in the work of Tabatabai and Shore (2005), those with higher levels of prior knowledge engaged in a greater number of information problem solving strategies during web searches in that they regularly changed strategy and navigated more frequently. Although framed as a comparison between experts and novices, learners with greater domain expertise have also been found to spend longer within a search session (White et al., 2009). Thus, it is reasonable to assume that the amount of prior knowledge that a learner holds about the topic at-hand will play a role in their information problem solving behaviour.

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1.2.2 External Conditions and Information Problem Solving

Specification of search terms can be regarded as a predominant information problem solving strategy that dictates the breadth of information that could be accessed (Walraven et al., 2008). Given that keyword searches have limited scaffolding, the individual requires the necessary skills to both specify appropriate terms and judge the results received (Walraven et al.). As discussed previously, search tools require, but are not limited to, learners making use out of Boolean operators and a continual need to evaluate information sources (Ivanitskaya et al., 2006; Judd & Kennedy, 2011). In both the works of Ivanitskaya et al. and Judd and Kennedy, there were few instances of participants incorporating Boolean operators into searches or going beyond a search involving a single keyword. As a tool for information problem solving, keyword searches can be viewed as requiring substantial skills in order to be effectively used.

Concept maps offer an alternate method for individuals to easily navigate a content space and develop a deeper understanding of the topic, particularly if prior-knowledge is low (Chen & Macredie, 2010; Minetou et al., 2008). As discussed in the meta-analytic work of Nesbit and Adesope (2006), the use of pre-constructed concept maps can help learners to recall central and detail ideas at a better rate compared to studying text passages (Schroeder, Nesbit, Anguiano, & Adesope, 2018). These benefits attained from using a concept map can be attributed to the requirement of greater learner engagement compared to tasks involving listening and reading. Moreover, by acting as a scaffold, concept maps can improve learner comprehension by breaking a topic into manageable chunks (Patterson, 2001). As for those with higher levels of prior knowledge, existing research has also found that these learners can also benefit from being more focused when using a concept map than those with lower prior knowledge levels (Amadieu, van Gog, Paas, Tricot, & Marine, 2009). In contrast to keyword searches, concept maps do not require the same level of skill when it comes to navigation and can be scaffolded.

As detailed above, search tools offer minimal direction for an individual to construct accurate queries, whilst concept maps allow the user to easily navigate the topic space. From an information problem solving perspective, it is therefore important to explore how variations in the scaffolds afforded by each tool are associated with the behaviours enacted.

1.3   Information Problem Solving and Outcomes

Being a successful learner is attributed to making accurate judgements with regards to knowing the material under study (Bjork, Dunlosky, & Kornell, 2013; Jemstedt, Kubik, & Jönsson, 2017). Entwined within such judgements are an individual's perception of their task performance (Hacker, Bol, & Keener, 2008), which can be compared against actual performance as means of assessing calibration. Put another way, calibration refers to the alignment between an individual's perceived and actual performance; it is, in effect, a metacognitive monitoring process (Bol & Hacker, 2012). In cases of over-confidence, where a student may be overly optimistic, this may result in early termination of studies and detriment of their scholastic achievement (Dunlosky & Rawson, 2012). Failure to then dedicate enough time to the pursuit of understanding a topic could then be attributed to a distorted perception of confidence (Hacker et al., 2008). For the current purpose, the importance of considering confidence judgements is based on understanding whether they are associated with the information problem solving strategies. In doing so, it would provide a means of exploring whether enacted strategies are attributed to perceptions of performance within a task.

Continued usage of a particular technology is associated with an individual's experience of the tools themselves, specifically whether they are perceived to be useful (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012). On this basis, the researchers sought to explore whether the extent to which students' engagement with both the concept map and search tool are associated with usefulness perceptions. This is important from a self-regulated learning perspective as refers to conditional knowledge, which encompasses utility judgements about a particular strategy (Butler & Winne, 1995). These perceptions then become internal conditions that consequently affect the information problem solving strategies enacted in the future (Winne, 2017). Clarebout, Elen, Collazo, Lust, and Jiang (2013) consider perceived usefulness as a valid proxy for metacognitive knowledge and showed it to be a reliable predictor of tool usage. Put differently, by engaging with the tool an individual builds up an understanding of how it can be a benefit to their learning, which then informs future decisions on whether to use the tool or not.

In addition to exploring utility perceptions, the research explored how learners perceive their performance in an information problem solving to be with regards to accuracy and validity (Hacker et al., 2008; Luyten & Dolkar,

2010). Prior work has explored the calibration between self-reported achievement and actual achievement in learners; results showed some learners to be overconfident in their perceptions (Winne, 2010; Winne & Jamieson-Noel, 2002). What can be inferred from these findings is that not all learners are able to effectively calibrate their achievement perceptions, representing problems with their ability to self-regulate, specifically in relation to monitoring. For the present purpose, measuring perceived achievement was essential to understanding whether it was associated with information problem solving behaviour. Put differently, it would enable the researchers to understand whether the self-regulatory behaviour of the learners was associated with their ability to monitor achievement.

1.4 Research Questions

For the purpose of this work, the model of Winne, Vytasek, et al. (2017) and recommendation of Winne (2019) were followed. Put differently, the work sought to trace learner actions during a information problem solving task (using a concept map to answer an essay question) with a view of discussing how this can then be used to provide actionable feedback. In addition to describing the strategies enacted as learners information-problem solve, the current exploratory work sought to answer three research questions:

1. Based on the traces of data collected following participants use of both concept maps and search tools to complete an information problem solving task, can meaningful information problem solving strategies be identified and if so, what are their characteristics?

2. Are the identified information problem solving strategies associated with any post-study outcomes including essay scores?

3. Are final measured outcomes associated with information problem solving strategies, motivations, and prior knowledge?

These three research questions were selected as the respective answers would address gaps in the literature. For one, approaches to understanding enacted information problem solving strategies are not standardised and vary between self-reports, traces, and think-alouds. What is anticipated from the answers to research question one is an understanding of whether the integration of results from two approaches (self-reports and traces) would

offer deeper insights than either approach in isolation. As for research question two, the answer would show whether particular patterns of information problem solving are associated with performance measures. In doing so, this adds validity to the application of trace methodologies to extract meaningful strategies that may be attributed students' academic outcomes. As for research question three, this seeks to reiterate the importance of a combined methodological approach wherein the advantages of self-report and trace methodologies are leveraged. Findings will also be used to evaluate models of information problem solving (e.g., Winne, Vytasek, et al., 2017) to understand the effects of conditions and strategies on final outcomes.

2 Method

2.1 Participants

A self-selecting sample of 111 students from two polytechnic and applied sciences higher education institutions in Canada partook in the study; no demographic data from this sample was recorded so cannot be provided.

2.2 Data Collection

2.2.1 Questionnaires

Six questionnaires were used for this research, three were administered prior to the information problem solving task (the *Achievement Goal Questionnaire*, *Need for Cognition Scale*, and a *Perceived Prior Knowledge Scale*) and the remaining three were given on completion of the information problem solving activity (*Perceived Usefulness of the Concept Map*, *Perceived Usefulness of the Search Tool*, and *Self-Evaluation*). Those questionnaires administered at the beginning of the study were used to answer Research Question 1 (association between internal conditions and information problem solving strategies), Research Question 2 (effect of information problem solving strategies of post-study outcomes) was to be answered by the data obtained from the post-study questionnaires, and both pre- and post-study questionnaires were used to address Research Question 3 (effect of internal conditions and information problem solving strategies on post-study outcomes). For all scales used, responses were made on 5-point Likert scales (1 = Strongly Disagree; Strongly Agree = 5).

The *Need for Cognition Scale* used was the revised 18-item version developed by Cacioppo et al. (1984) due to the need of creating an efficient scale (Appendix 1). Selection of this scale was motivated by prior work identifying need for cognition as a trait associated with the extent to which an individual engages in self-regulatory behaviour (Cazan & Indreica, 2014). Based on the work of Cacioppo et al. (1984), the instrument is purported to measure a single underlying construct of the Need for Cognition; a Cronbach's α value of .90 was also recorded for this unidimensional construct. For the current study, the Cronbach's α was calculated as -.02, which presented an issue with the scale and a decision was made to not utilise the *Need for Cognition Scale* any further.

To measure participants' achievement goal orientations the 18-item instrument developed by Elliot and Church (1997) was adapted for the current purposes (e.g., the word class was changed to study; Appendix 2). Selection of this scale was based on it measuring task-specific motivation, specifically whether the individual seeks to display competency or become proficient at the task (Elliot et al., 2011). The factor model presented by Elliot and Church (1997) showed that the scale measures three underlying constructs (*Mastery Goal*, *Performance-Approach Goal*, and *Performance-Avoid Goal*) using six items per construct. Elliot and Church (1997) also found the Cronbach's α for each of the measured constructs to be acceptable, with values of .89, .91, and .77 for *Mastery Goal*, *Performance-Approach Goal*, and *Performance-Avoid Goal*, respectively. Acceptable Cronbach's α values were found for the current work: .94 for *Mastery Goal*, .92 for *Performance-Approach Goal*, and .93 for *Performance-Avoid Goal*; the scale was retained based on these results.

Perceived Prior Knowledge was measured using six items (Appendix 3); the items were not taken from any pre-established scale. For the purposes of this study, the need for a scale measuring prior knowledge was essential to explore whether essay scores or behaviour may have been affected by knowledge levels. It is, however, important to note that this approach of creating an *on-the-fly* scale is not recommended (Flake & Fried, 2019) as it raises questions about the validity of any presented findings. To address these issues the responses to these six items were subject to exploratory factor analysis (Appendix 4), which showed a one-factor solution to be acceptable; a Cronbach's α value of .84 was obtained for this scale.

On completion of the information problem solving task, participants were given two self-evaluation items (Appendix 5) to assess whether they perceived

their essay answers to be accurate and valid. These two items were chosen to be representations of confidence judgements (Hacker et al., 2008) that would offer insights into student calibration. Put differently, these items aimed to explore student perceptions of whether their answer was closely aligned to the what was expected (accuracy) and addressed the question set (validity). As with the perceived prior knowledge items, these self-evaluation items were not based on pre-existing scales. Any associated finding related to these confidence judgements should remain tentative, pending the need for a valid measure.

The remaining two sets of items were used to measure participants' perceived usefulness of the concept map and the search tool (six items per construct; Appendix 6 and 7). The items themselves were adapted from the perceived usefulness scale created by Davis (1989), which originally received a Cronbach's α value of .98. For the current study, the Cronbach's α values for perceived usefulness were .28 and .27 for the concept map and search tool, respectively. On this basis, the data collected using these scales were not incorporated into any further analyses due to the identified issues.

To summarise, problems were identified with the need for cognition scale and both perceived usefulness scales; therefore, data collected using these instruments was omitted from any further analyses. Only data collected through the achievement goal orientation, perceived prior knowledge, and post-evaluation instruments were utilised in the analyses that follow.

2.2.2 Log Data

Throughout the study, participants had access to both a *concept map* and *search tool* that were intended to assist them in the writing of an essay. All interactions with these tools were recorded, specifically in the form of four events: ConceptMap.ViewTerm, ConceptMap.ViewLinkURL, Search.ViewQuery, and Search.ViewLinkURL (Table 1). Each of these actions were timestamped and associated with unique participant identification (ID) numbers.

2.2.3 Essay Score

The overall aim of the information problem solving task was for participants to utilise the available tools (*concept map* and *search tool*) to gather information for the purpose of answering two questions. All essay answers were

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Table 1: Information Problem Solving Strategies Extracted from the Data

Action Code	Description
ConceptMap.ViewTerm	Viewing a term contained within the concept map
ConceptMap.ViewLinkURL	Viewing a link contained within the concept map
Search.ViewQuery	Viewing a query returned from the search tool
Search.ViewLinkUrl	Viewing a link returned from the search tool

graded using an analytical type rubric with a single point being awarded for each of the following: an accurate answer was given, the argument was logical and clearly articulated, and the answer was coherent. If an element of the rubric was not addressed by a participant's essay answer then they were awarded a zero for that criteria. Essay evaluators were not aware of how much time students had spent writing the essays, nor did they have any information on how the essay was written.

2.3   Procedure

The study itself involved three stages that consisted of six questionnaires and an information problem solving activity; the procedure overview is presented in Figure 1. At the start of the study the initial step was for participants to complete three questionnaires that measure *Achievement Goals*, *Need for Cognition*, and *Prior Knowledge* about the subject. Following the completion of the instruments, participants were then given an hour to write a short essay (200-300 words) on two questions:

1. Describe, in simple language, what a security exploit is.

2. Provide an example of how a security exploit might impact a person.

This essay topics was selected as they presented a topic that was, to some extent, obscure. Topic was also intended to be deep enough for meaningful answers to be given and would therefore motivate participants to utilise the tools that were provided (a *concept map* and a *search tool*; Figure 2).
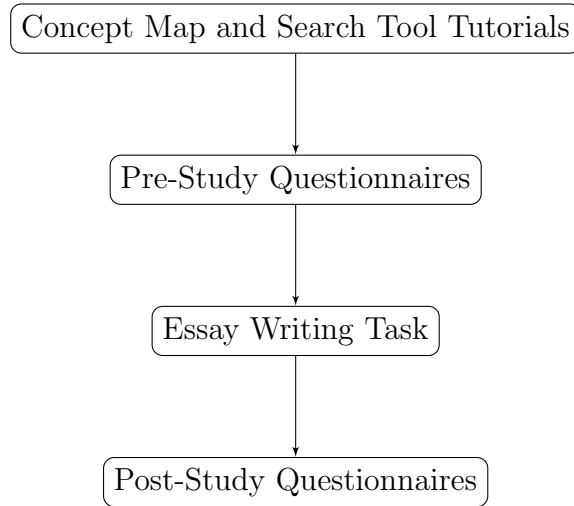
Figure 1: Flow Chart showing the Study Procedure

Creation of the *concept map* followed the guidelines outlined by Novak and Cañas (2008) wherein an initial search of "*Security Exploits*" was performed using a Google Custom Search Engine. Results returned from the search query were then parsed for the purpose of creating a database of keywords; words were filtered down to those consisting of more than four characters. A series of concept maps were then created using the keyword database, with edges between web pages being informed by the number of overlapping keywords. This was an iterative process, as sparse and dense networks were obtained when the number of matching keywords were at five or ten, respectively. An optimum was found for eight overlapping keywords as this resulted in a network with a sensible number of edges that would not substantially impede either readability or navigation. When navigating the concept map, clicking on a concept (a node) would provide the student with a series of web links for pages that were associated; position within the list was determined by the keyword database ranking.

The *search tool* used was based on the Google Custom Search Engine technology. In doing so, we were able to restrict the search space to prevent students from being overloaded with information. Moreover, the *search tool* allowed for the capturing of search queries, page views, and the time at which the page was viewed for each student.

Prior to writing the essay task participants were allowed time to gain

experience using these tools (*concept map* and *search tool*) so that any technical issues could be addressed. In addition, participants were also presented with a short tutorial that provided guidance on how to utilise both tools. Following the completion of the essay writing task, participants were then presented with two questionnaires aimed at measuring *Perceived Usefulness* of both the *concept map* and *search tool*. In addition, two questions were presented to participants for the purpose of self-evaluating their own answers to the essay questions.

2.4 Data Analysis

2.4.1 Research Question 1

To address research question one, which aimed to identify and characterise the information problem solving strategies used by students during an essay writing task, event sequence analysis was carried out using the TraMineR package in R (Gabadinho, Ritschard, Müller, & Studer, 2011).

For each student participating in the study, trace data was collected as they engaged with both the concept map and search tool. This corresponded to one of four actions: Search.ViewLinkURL, Search.ViewQuery, ConceptMap.ViewTerm, and ConceptMap.ViewLinkURL; these events were analysed using event sequence analysis. As the aim was to explore the information problem solving strategies enacted by students, all event sequences were initially plotted as a means of visualising how student actions varied over the course of the essay writing task. This visualisation of the event sequences was then supplemented with descriptive statistics showing the frequency at which the sample of students engaged in each record action; details about time-on-task were also provided. Given the growing trend of applying temporal analyses to understand learning as a dynamic system (Molenaar & Järvelä, 2014; Knight, Wise, & Chen, 2017), the current work is well placed. In particular, the analysis presents information problem solving as a sequence of behaviours that are enacted over the course of the study.

Following the prior work undertaken by Matcha, Gašević, Ahmad-Uzir, Jovanović, and Pardo (2019), which showed learners to be heterogeneous with regards to their information problem solving strategies, we sought to segment the event sequences using agglomerative hierarchical cluster analysis in our aim to identify information problem solving strategies. The decision to use agglomerative hierarchical cluster analysis was further based on the reasons
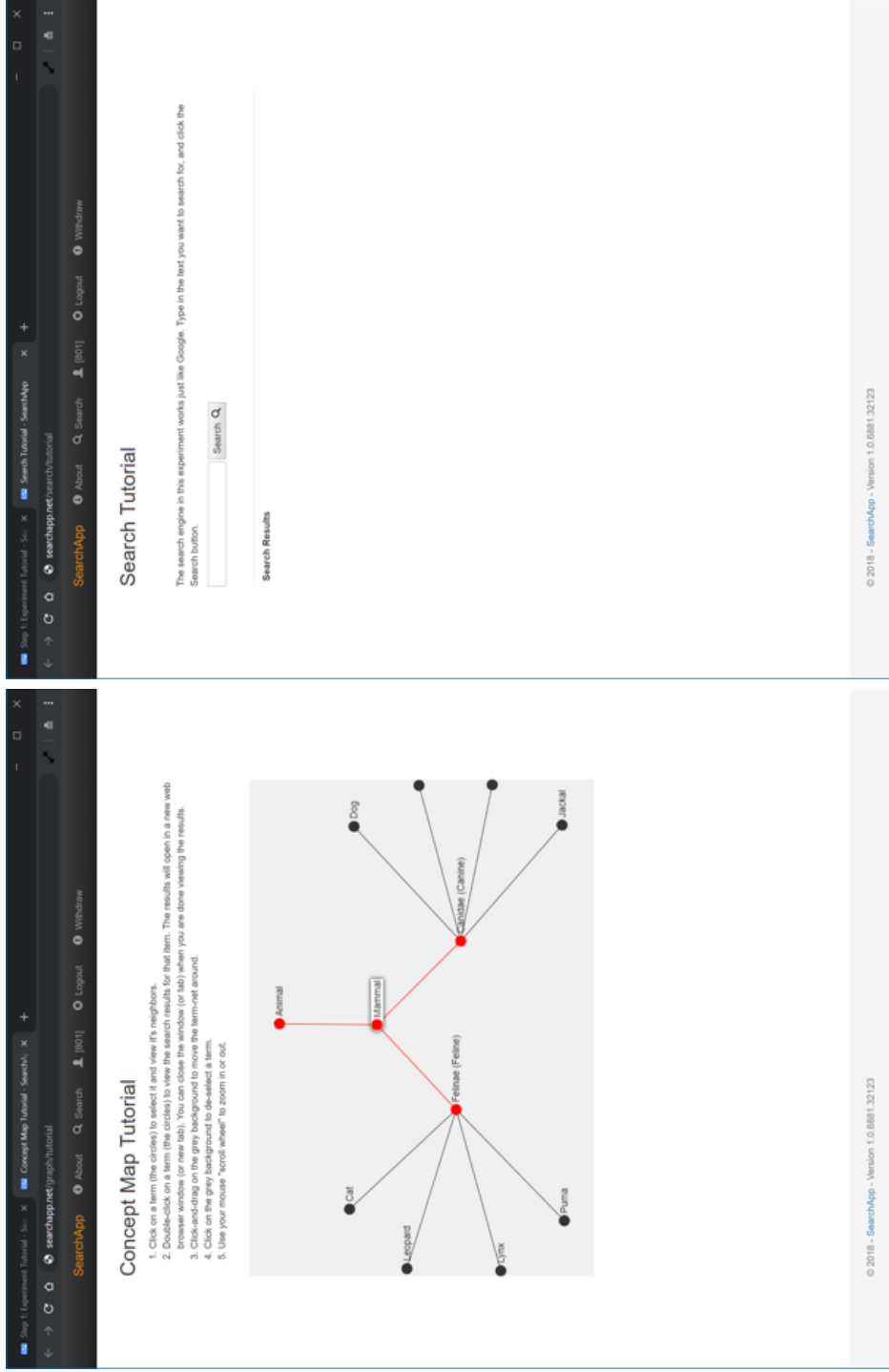
Figure 2: Concept Map and Search Tool Provided to Students

outlined by Kovanović, Gašević, Joksimović, Hatala, and Adesope (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, Gašević, Jovanović, & Pardo, 2018; Kovanović et al., 2015). 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.

After the identification of a suitable cluster solution, the differences between the clusters were explored through descriptive statistics, representative sequence plots, and first-order Markov models. The descriptive statistics were frequency measures for each of the four recorded actions (Search.ViewLinkURL, Search.ViewQuery, ConceptMap.ViewLinkURL, and ConceptMap.ViewTerm). The representative sequences were 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; Gabadinho et al., 2011). 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 had a representative within their neighbourhood. Thus, for each cluster there could be different numbers of representatives for the 25% threshold to be met. These 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 first-order Markov models were fitted to each identified cluster using the seqhmm package (Helske & Helske, 2019) 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 were compared across the retained pre-study measures collected (Mastery Goal, Performance-Approach Goal, Performance-Avoid Goal, and Perceived Prior Knowledge). Average scores were computed for each of these four 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 four pre-study predictor variables.

2.4.2 Research Question 2

Research question two sought to explore whether the identified information problem solving strategy groups differed in regards to the measured post-study variables. Initially, six post-study variables were collected; however, two measures (perceived usefulness of the concept map and search tool) were identified as being problematic and so were subsequently dropped. T-tests were used to compare the identified clusters across the four retained measures (time-on-task, essay score, perceived essay answer accuracy, and perceived essay answer validity).

2.4.3 Research Question 3

Research question three aimed to explore whether any of the four learning actions (Search.ViewLinkURL, Search.ViewQuery, ConceptMap.ViewTerm, and ConceptMap.ViewLinkURL), motivations, or perceived prior knowledge were associated with two post-study outcomes (perceived essay answer accuracy, and perceived essay answer validity). As with research question two, two measures were dropped due to issues with their reliability (perceived usefulness of the concept map and search tool). With the retained measures of perceived essay answer accuracy and validity, these were regressed onto five predictor variables (cluster assignment, mastery goal, performance-approach goal, performance-avoid goal, and perceived prior knowledge). For the purposes of this current work, the alpha level was set at .05.

3 Results

3.1 Research Question 1

Essay task times ranged from 445 seconds to 4,843 seconds with an average completion time of 1998.88 seconds ($SD = 1451.90$; a distribution of these times is presented in Appendix 8). Table 2 presents the counts and percentages for each of the four actions measured during the course of the information problem solving activity (Search.ViewLinkURL. Search.ViewQuery, ConceptMap.ViewLinkURL, and ConceptMap.ViewTerm). Based on the

Table 2: Action Counts and Percentages

Action	n	%	M	SD
Search.ViewLinkURL	2217	23.20	20	3
Search.ViewQuery	741	7.74	6.68	4
ConceptMap.ViewLinkURL	5280	55.20	47.60	12
ConceptMap.ViewTerm	1331	13.90	12	7

frequencies alone, ConceptMap.ViewLinkURL was the most common action as it occurred 55.20% (n) of the time. This was followed by Search.ViewLinkURL ($n = 2217$, 23.20%), ConceptMap.ViewTerm ($n = 1331$, 13.90%), and then Search.ViewQuery ($n = 741$, 7.74%).

Across the sample of participants, the number of actions undertaken ranged from 37 to 174; the mean number of actions equalled to 86.20 ($SD = 40.60$). A visualisation of the event sequences for the whole sample is presented in Figure 3. The y-axis of this figure represents each of the 111 students and the x-axis is each recorded step in the information problem solving activity (starting from the first step to the last step). Each line is therefore a representation of the activities undertaken by a single student in the information problem solving activity - the activity undertaken is denoted by one of four colours. As can be seen in this plot, all participants start with the ConceptMap.ViewTerm action and then move to ConceptMap.ViewLinkURL action; switching between these two actions occurred frequently for a majority of the information problem solving task. It is only at the later stages of the information problem solving activity that participants began to use the Search.ViewLinkURL and Search.ViewQuery actions.

The visualisation of events presented in Figure 3, in combination with the distribution of time spent on task (Appendix 8), does suggest that participants were not alike in their use of information problem solving strategies. For example, some participants spent a longer period of time completing the information problem solving activity or engaged in greater number of actions. To explore differences in enacted strategies during the information problem solving activity in further detail, the next step was to analyse event sequences with hierarchical cluster analysis.

A dissimilarity matrix was created using the optimal matching method and a substitution cost of 1 for the purpose of running the hierarchical cluster analysis. The dendrogram obtained from this is presented in Appendix 9, which suggested that a two-cluster-solution would be a suitable cut-off.
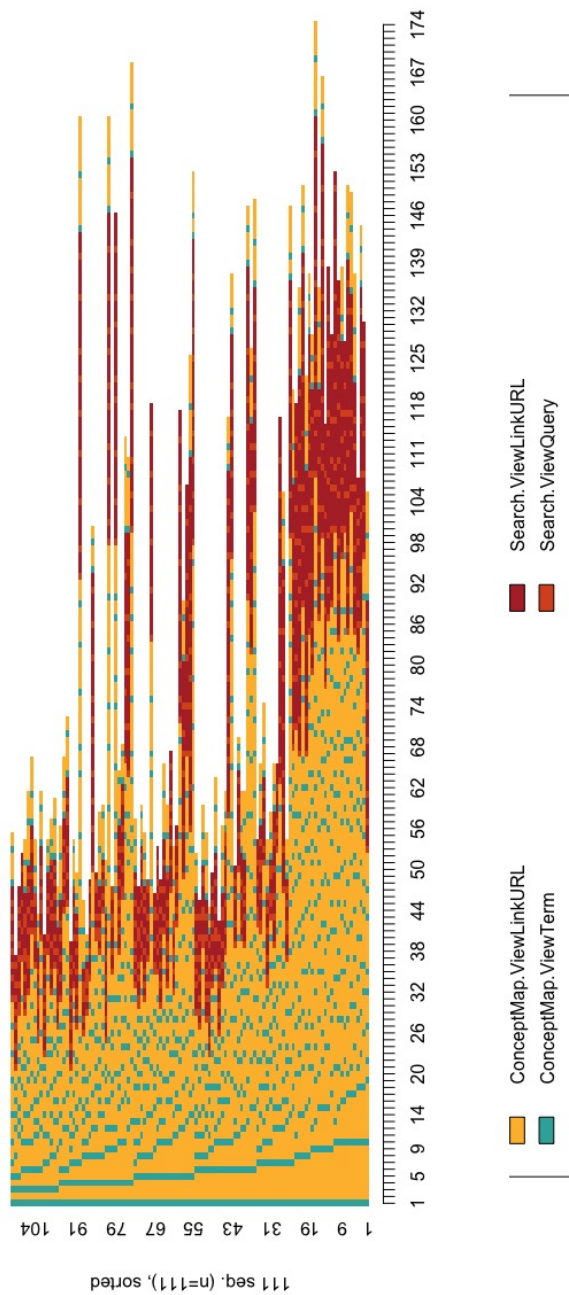
Figure 3: Plot of event sequences for the whole sample ($n = 111$)

To determine whether the two-cluster solution was interpretable, a representative sequence plot was used to explore how the two groups differed (Figure 4). Based on this plot, the first group (left plot in Figure 4) was assigned the label the High Engagement Group as the event sequences were long in length. Whereas, the second group (right plot in Figure 4) was labelled the Low Engagement group given the short sequence lengths defining the cluster. The High Engagement group was made up of 45 participants and was represented by 12 event sequences, which gave a 26.70% coverage (left plot in Figure 4). These 12 event sequences showed that the High Engagement participants initially started with a ConceptMap.ViewTerm action, which was then followed by a pattern of switching between the ConceptMap.ViewTerm and ConceptMap.ViewLinkURL actions. It was only towards the end of the event sequences that the High Engagement group started to display the Search.ViewQuery and Search.ViewLinkURL actions. The Low Engagement group, on the other hand, included 66 participants and was represented by a single event sequence that gives a 30.30% coverage (right plot in Figure 4). Although different in sequence length, when compared to the High Engagement group, the Low Engagement group representative sequence was similar. The representative sequences indicated participants initially switched between the actions of ConceptMap.ViewTerm and ConceptMap.ViewLinkURL. Then, towards the end of the event sequence, students then began to engage in Search.ViewQuery and Search.ViewLinkURL actions.

Descriptive statistics for the two groups (High Engagement and Low Engagement) are presented in Table 3, which gives a more detailed understanding as to how they differ. For both groups, the most common action within the information problem solving task was ConceptMap.ViewLinkURL, which made up 56.20% (n = 3,340) and 53.60% (n = 1940) of actions for both the High and Low Engagement groups, respectively. In addition, the ConceptMap.ViewLinkURL 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 Search.ViewLinkURL for the High Engagement group (M = 35.40, SD = 7.41, n = 1,595, 26.80%), whilst for the Low Engagement group it was ConceptMap.ViewTerm (M = 10.20, SD = 1.41, n = 672, 18.60%). The third most frequent action for the High Engagement group was ConceptMap.ViewTerm (M = 14.60, SD = 2.60, n = 659, 11.10%) and for the Low Engagement group it was Search.ViewLinkURL
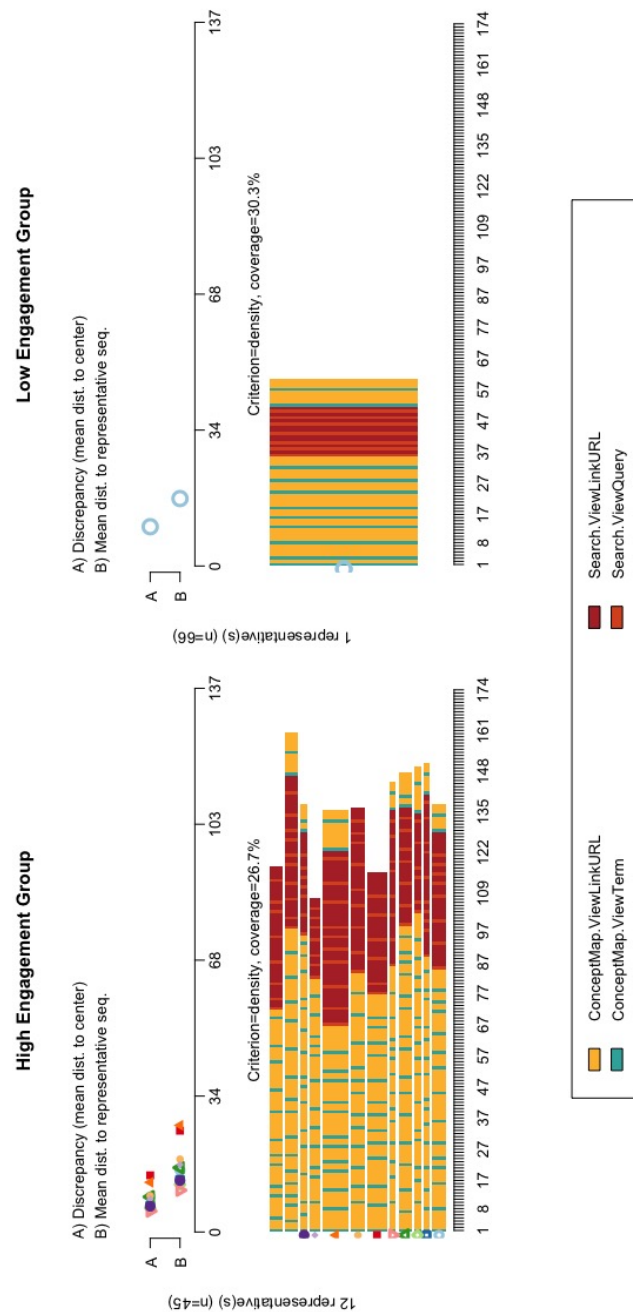
Figure 4: Representative Sequence Plots for the High and Low Engagement Groups

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($M = 9.42$, $SD = 2.50$, $n = 622$, 17.20%). Finally, Search.ViewQuery 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 a suitable cut-off for the current work.

The next step of the analysis was to explore how participants within these two clusters moved between the four observed states using a first-order Markov model; Figures 5 and 6 present the first-order Markov models for the two clusters (the High and Low Engagement groups). For each Markov models, it is clear that participants started the information problem solving task with the ConceptMap.ViewTerm action and then switched to the ConceptMap.ViewLinkURL action. For those in the High Engagement group, there was an .810 probability of continuing with the ConceptMap.ViewLinkURL action, which reduced to .669 for the Low Engagement group. When switching from the ConceptMap.ViewLinkURL action back to the ConceptMap.ViewTerm action, the Low Engagement group had a higher transition probability (.296) than the High Engagement group (.176). As for switching from either the ConceptMap.ViewTerm action to the Search.ViewQuery or Search.ViewLinkURL actions, the transition probabilities were 0 for both the High and Low Engagement groups. As for transitioning from the ConceptMap.ViewLinkURL action to either the Search.ViewQuery or Search.ViewLinkURL actions, the transition probabilities were low for both the High (.014 and .000, respectively) and Low (.035 and .000, respectively) Engagement groups.

As for moving from the Search.ViewQuery action on to the Search.ViewLinkURL action, there was a transition probability of 1 for participants of the High Engagement group; whereas, the probability of remaining in Search.ViewQuery state was 0. In the case of the Low Engagement group, the transition probability from Search.ViewQuery to the Search.ViewLinkURL was .852, whilst the probability of remaining in the Search.ViewQuery state was .130. With regards to transition probabilities for switching from the Search.ViewQuery action to either ConceptMap.ViewTerm or ConceptMap.ViewLinkURL, these were 0 for the High Engagement group; the Low Engagement group had transition probabilities of 0 and .018 for ConceptMap.ViewLinkURL and ConceptMap.ViewTerm, respectively. Finally, with regards to the Search.ViewLinkURL action, the High Engagement group had transition probabilities of .786, .195, 0, and .020

Table 3: Descriptive Statistics for the High and Low Engagement Groups

Cluster Variable	Variable	n	%	M	SD
High Engagement	Search.ViewLinkURL	1595	26.80	35.40	7.40
	Search.ViewQuery	353	5.94	7.84	1.59
	ConceptMap.ViewLinkURL	3340	56.20	74.20	15.20
	ConceptMap.ViewTerm	659	11.10	14.60	2.60
	Time-On-Task*	-	-	3618.93	613.54
	Performance-Approach	-	-	2.19	.48
	Performance-Avoid	-	-	2.06	.53
	Mastery	-	-	2.00	.46
	Prior Knowledge	-	-	3.40	.46
	Answer Accuracy	-	-	4.42	.66
	Answer Validity	-	-	3.80	.73
Low Engagement	Search.ViewLinkURL	622	17.20	9.42	2.50
	Search.ViewQuery	388	10.70	5.88	1.14
	ConceptMap.ViewLinkURL	1940	53.60	29.40	7.65
	ConceptMap.ViewTerm	672	18.60	10.20	1.41
	Time-On-Task*	-	-	831.77	242.97
	Performance-Approach	-	-	3.49	.81
	Performance-Avoid	-	-	3.56	.92
	Mastery	-	-	3.61	.94
	Prior Knowledge	-	-	2.58	.56
	Answer Accuracy	-	-	4.38	.65
	Answer Validity	-	-	3.89	.64

*Mean and standard deviation values refer to seconds

for Search.ViewLinkURL, Search.ViewQuery, ConceptMap.ViewLinkURL, and ConceptMap.ViewTerm, respectively. Whereas, for the Low Engagement group, the transitions probabilities from the Search.ViewLinkURL to Search.ViewLinkURL, Search.ViewQuery, ConceptMap.ViewLinkURL, and ConceptMap.ViewTerm were .486, .451, 0, and .063, respectively.

To explore how the two identified clusters (High and Low Engagement groups) differed with regard to background characteristics (Mastery Goal, Performance-Approach Goal, Performance-Avoid Goal, and perceived prior knowledge), four comparisons were made. There was a significant difference between the High ($M = 2.19$, $SD = .48$) and Low ($M = 3.49$, $SD = .81$) Engagement groups with regards to Performance-Approach Goal orientation; $t(106.82) = 10.63$, $p < .001$, d = 1.97. Similarly, the groups significantly differed with regards to both the Performance-Avoid Goal orientation (High Engagement group: $M = 2.06$, $SD = .53$; Low Engagement group: $M = 3.56$, $SD = .92$; $t(106.23) = 10.883$, $p < .001$, d = 2.00) and Mastery Goal orientation (High Engagement group: $M = 2.00$, $SD = .46$; Low Engagement group: $M = 3.61$, $SD = .94$; $t(100.24) = 11.999$, $p < .001$, d = 2.18) 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 ($M = 2.58$, $SD = .56$); $t(105.43) = -8.340$, $p < .001$, d = 1.60.

3.2   Research Question 2

The two clusters (High and Low Engagement groups), identified on the basis of the recorded event sequences, were then compared on two variables: time-on-task and 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 ($M_{Seconds} = 3670.07$, $SD_{Seconds} = 613.61$) were significantly different from the Low Engagement group ($M_{Seconds} = 859.44$, $SD_{Seconds} = 246.44$); $t(53.77) = 29.165$, $p < .001$, d = 6.01.

Comparisons between the two groups (High and Low Engagement) were also made on two post-study variables (perceived essay task accuracy and perceived essay task validity). The results showed there to be no significant differences between the two groups on 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), or perceived essay task
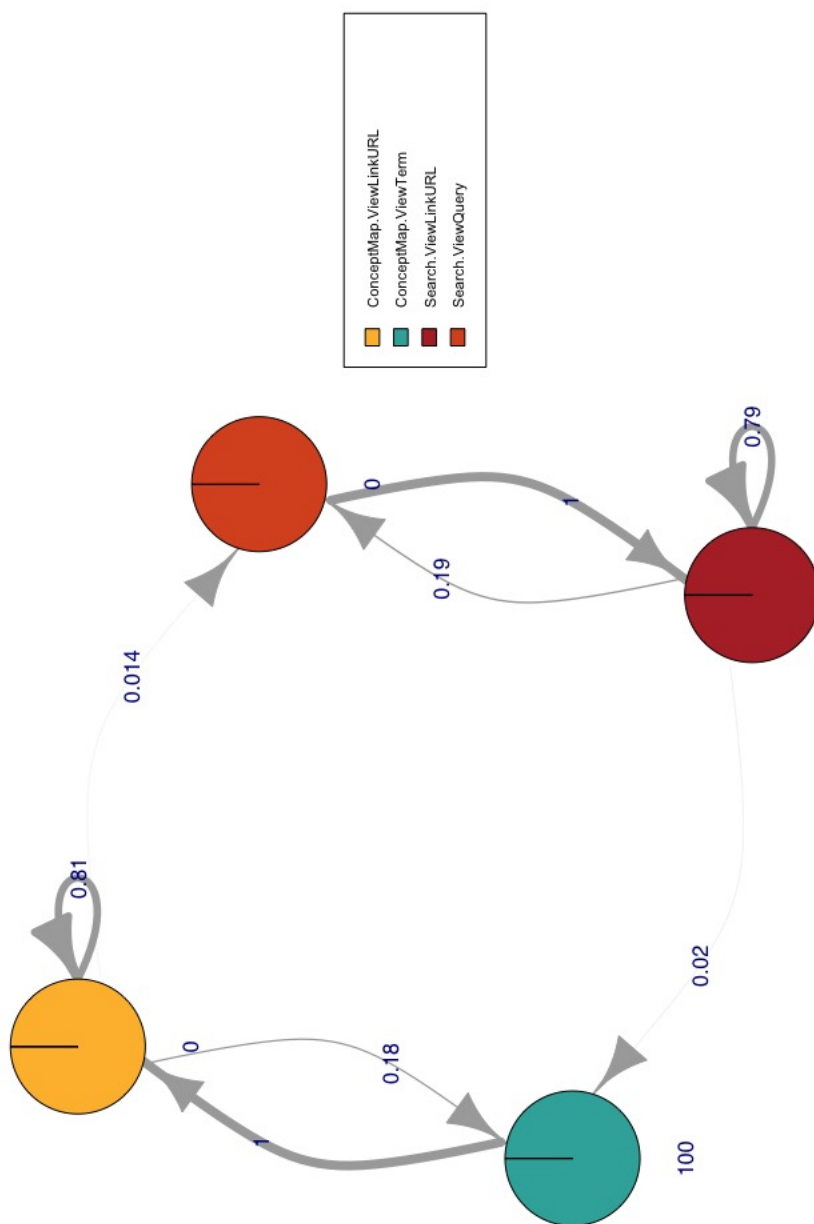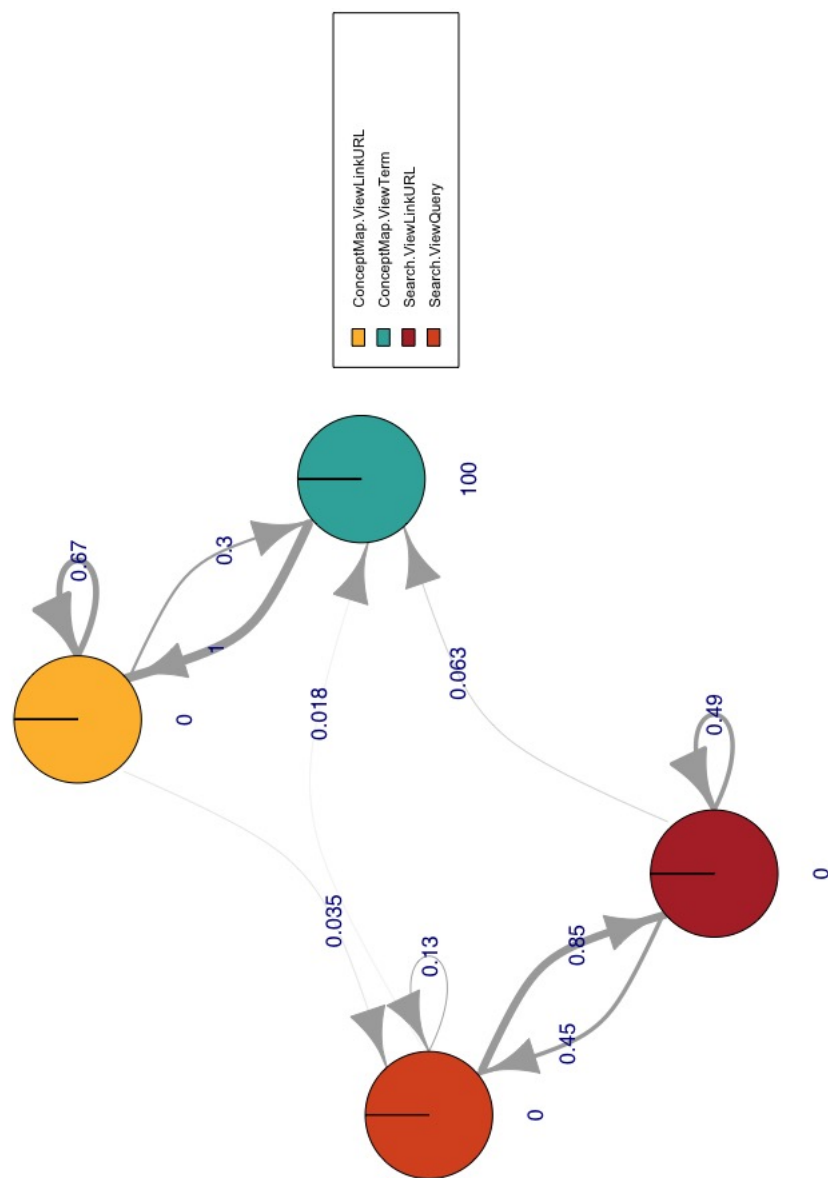
Figure 5: Markov Model Plot for the High Engagement Groups

ConceptMap.ViewLinkURL
ConceptMap.ViewTerm
Search.ViewLinkURL
Search.ViewQuery

Figure 6: Markov Model Plot for the Low Engagement Groups

Table 4: Predicting the Probability of Cluster Assignment

Variable	Estimate	Standard Error	Z-Value	P-Value
Intercept	1.993	3.014	.661	.509
Performance-Approach	-.032	.754	-.042	.966
Performance-Avoid	-.492	.610	-.807	.420
Mastery	-1.298	.656	-1.979	.048
Prior knowledge	.834	.708	1.179	.238

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 regressed on four predictor variables (Performance-Approach Goal orientation, Performance-Avoid Goal orientation, Mastery Goal orientation, and perceived prior knowledge). The output of the logistic regression model is presented in Table 4, which only shows that a one-unit increase in Mastery Goal orientation being associated with a decrease in log odds of being assigned to the High Engagement group by 1.298 units. Put differently, students with higher Mastery Approach orientation were less likely to be in the High Engagement group. No other predictor variable was found to be associated with cluster assignment at the 5% level. Although not statistically significant, the predictors were retained in the model on account as they convey important information.

3.3 Research Question 3

Two dependent variables (perceived essay answer accuracy and perceived essay answer validity) were regressed onto eight predictor variables (Search.ViewLinkURL, Search.ViewQuery, ConceptMap.ViewLinkURL, and ConceptMap.ViewTerm, Performance-Approach goal, Performance-Avoid goal, Mastery goal orientation, and perceived prior knowledge). For all models ran, the F-statistics were smaller than 1 with p-values exceeding .05, and adjusted R^2 values approximately equalled to 0. The outputs of the four regression models are presented in Tables 5 and 6.

Table 5: Linear Regression Model Predicting Essay Answer Accuracy

Variable	Estimate	Standard Error	T-Value	P-Value
Intercept	3.878	.833	4.656	<.001
Search.ViewLinkURL	-.004	.014	-.317	.752
Search.ViewQuery	.011	.069	.153	.879
ConceptMap.ViewLinkURL	-.008	.011	-.713	.478
ConceptMap.View	.057	.067	.856	.394
Performance-Approach	-.081	.166	-.485	.629
Performance-Avoid	.014	.139	.099	.922
Mastery	-.013	.143	-.094	.925
Prior Knowledge	.155	.153	1.018	.311
Multiple R^2: .041		Adjusted R^2: -.035		
$F(8, 102) = .540, p = .824$				

Table 6: Linear Regression Model Predicting Essay Answer Validity

Variable	Estimate	Standard Error	T-Value	P-Value
Intercept	3.090	.850	3.635	<.001
Search.ViewLinkURL	.016	.014	1.111	.269
Search.ViewQuery	-.011	.070	-.151	.880
ConceptMap.ViewLinkURL	-.025	.011	-2.254	.026
ConceptMap.View	.114	.068	1.670	.098
Performance-Approach	-.036	.170	-.214	.831
Performance-Avoid	.021	.142	.150	.881
Mastery	-.005	.146	-.034	.973
Prior Knowledge	.131	.156	.846	.400
Multiple R^2: .064		Adjusted R^2: -.010		
$F(8, 102) = .867, p = .547$				

4 Discussion

The current work sought to provide an answer to three research questions. Firstly, the findings showed that through the capturing of event traces from both concept map and search tool, meaningful information problem solving strategies can be identified and characterised (Research Question 1). Secondly, it was found that the information problem solving strategy taken by participants does have an effect upon the post-study outcomes of essay grade and time-on-task, both of which had large effect sizes (Research Question 2). Lastly, it was found that participant perceptions of their answers given to the essay questions were not affected by their information problem solving approach, motivations, nor their levels of prior knowledge (Research Question 3).

Simply focusing on the identification of two information problem solving groups, it would appear that this is a confirmation of the findings presented by Raes et al. (2010). In other words, there is one group of learners who engage in a greater number of information seeking activities (effective information problem solving group), whilst the other group does not display this level of behaviour (ineffective information problem solving group; Research Question 1). However, it is only the frequency at which the information seeking behaviours between the two group appear to be different; the ordering of the displayed behaviour was seemingly consistent. For both groups, the general sequence of strategies used in both groups showed a preference for initially switching between the two ConceptMap behaviours (ViewTerm and ViewLinkURL); Search behaviours (ViewQuery and ViewLinkURL) exclusively appeared occurred at the later stages of the information problem solving task. To an extent, this represents a mix of Thatcher's (2008) "*Safe player*" and "*Link-dependent*" strategies wherein navigating hyperlinks is first adopted and then replaced by search engine usage, which could be motivated by either a narrowing or broadening of the information. Given that strategies applied by learners are continually monitored and adapted based on the demands of the learning environment, the strategy switches may have occurred to fit their situation (Rovers, Stalmeijer, van Merriënboer, Savelberg, & de Bruin, 2018). It could then be argued that learners may have exerted all of what they consider to be of value from the concept map (Brand-Gruwel et al., 2009); thus, utilisation of the search tool then became the strategy of choice.

It is only when the identified groups are compared on the basis of attained

essay scores that it becomes clear as to who can be considered as succeeding in applying information problem solving strategies (Research Question 2). In particular, the large effect size for differences in essay scores between the two identified groups could imply that the actions taken by the High Engagement group were more effective than those of the Low Engagement group. For instance, the High Engagement group, on average, viewed a greater number of term and search URLs so it could be argued that they gained a deeper understanding of the topic at hand.

An alternate explanation of essay grade differences refers to prior knowledge, as those within the High Engagement group were found to have higher levels (based on a comparison of mean values; Research Question 3). Although, as a predictor within the logistic regression model, prior knowledge was not statistically significant. The coefficient was, nevertheless, positive, which would be expected based on previous findings. Take the work of Amadieu et al. (2009), they found higher prior knowledge to be associated with greater attention to concept map elements that enable a deeper understanding of the topic. For search behaviour, prior knowledge has been found to affect information problem solving strategies (White et al., 2009; Monchaux, Amadieu, Chevalier, & Mariné, 2015), with higher levels being attributed to better navigation and planning (Tabatabai & Shore, 2005; Sanchiz, Amadieu, Fu, & Chevalier, 2019). The current data, to some extent, support this as the High Engagement group engaged in viewing search URL links at a greater frequency. It can tentatively be argued that levels of prior knowledge do affect the way in which learners approach an information problem solving task, specifically in terms of the strategies enacted. Despite this, the higher essay grades attained by the High Engagement group could be attributed to having a better understanding of the topic area; thus better outcomes were inevitable.

Adding to the above-mentioned findings is the large effect for time-on-task, with the High Engagement group spending a greater amount of time on the information problem solving task (Research Question 2). Given the greater number of actions the High Engagement group carried out, it was of no coincidence that more time was spent on the task. Nevertheless, it has been outlined by Chickering and Gamson (1987) that in order to master a topic the learner should dedicate a sufficient amount of time to the topic. Compared to the Low Engagement group, the High Engagement group was more effective in managing their time on the information problem solving tasks. Put differently, these learners may have recognised that to succeed in

the task a greater amount of time is required to gain a better understanding of the topic. This also aligns with the finding that information problem solving sessions are typically longer for experts (White et al., 2009), particularly as the High Engagement group was found to have greater prior knowledge, which may suggest a higher degree of expertise.

There is always the possibility that strategy adoption by students was not motivated by students' decision making processes or internal conditions, but the nature of the task itself. As identified in the model of Winne and Hadwin (1998), external conditions are an important determinant in the strategies that are enacted by learners. Therefore, the type of activity, tools provided, or even the guidance offered could have been important. For this work, these external conditions were not explored at any real depth, but there is a need for future studies to consider the impact of these variables.

Although prior work would suggest that those who are more inclined to deeply understand a topic (Mastery goal orientation) are more likely to regulate their learning (Pintrich et al., 2001; Senko, Hulleman, & Harackiewicz, 2011), this was not supported by the current results (Research Question 2). The logistic regression coefficient showed those in the High Engagement group had lower levels of Mastery goal orientation than those in the Low Engagement group, which is not the expected direction. It would be anticipated, based on the descriptions of Pintrich et al. (2001), that Mastery oriented individuals would be more inclined to set goals and change strategies. Instead, the model output showed those students who engaged in fewer information problem solving strategies, spent less time-on-task, and obtained lower grades to, on average, have higher Mastery orientation scores. On the face of it, this appears contradictory as those driven to understand a topic appeared to be worse off, but there are caveats that need to be considered. Previous work into the calibration between self-reports and trace data undertaken by Winne and Jamieson-Noel (2002), Winne and Jamieson-Noel (2003), and Zhou and Winne (2012) has shown that measures taken to not align particularly well; learners were biased in their self-reported use of study tactics. In the current work, it may be that learners were not accurate in reporting their Mastery goal orientations in that it did not align with how they actually approach information problem solving tasks. The other consideration to make is that the High Engagement group, on average, had higher prior knowledge and may consequently not be driven to understand the content. Whilst the Low Engagement group may have a greater motivation to master the topic, their lower prior knowledge would prevent any sufficient

evaluation of learning products (i.e., lower standards to judge information and written essays against). Additional work is required to further understand the interplay between prior knowledge and Mastery goal orientation.

Neither Performance goal orientations (Approach and Avoid) were statistically significant predictors of cluster assignment (Research Question 2). For Performance-Approach, the coefficient was relatively small with a large standard error. Given the data, Performance-Approach motivation does not appear to be important in relation to what strategies were undertaken by students in the task. For Performance-Avoid, the predictor is not statistically significant, but the negative sign is understandable. This particular construct is associated with a need to display competence (Elliot et al., 2011) and a lower likelihood of engaging in self-regulatory behaviour (Pintrich et al., 2001). Therefore, the propensity for High Engagement students to have lower Performance-Approach goal orientations is intuitive as they spent longer on-task and showed more diverse behaviour compared to the Low Engagement students.

A final point regarding achievement goal orientation refers to its presumed malleability in that changes can be induced by factors in the learning environment, to name but one example (Zimmerman & Schunk, 2012). The importance of this claim for this purpose is that the measure used here was taken at a single instance in time, which may not be suitable to capture the complexity of changes in achievement goal orientation and motivation during the task (Zhou & Winne, 2012; Martin et al., 2015; Jovanović, Gašević, Pardo, Dawson, & Whitelock-Wainwright, 2019; Hadwin & Webster, 2013). Student motivations captured at the start of the study may not be representative of their goal orientations at different stages over the course of the study. Ideally, surveys would be taken intermittently, but there is a risk of survey fatigue. A possible solution could then be to investigate how traced-self-reported measures (Zhou & Winne, 2012; Jovanović et al., 2019) can be integrated into information problem solving tasks (e.g., as tags associated with bookmarks) to study differences in motivation among students who follow different strategies. In doing so, it would both capture the dynamics of achievement goal orientations and avoid overloading students with surveys.

With regards to the retained post-study variables of perceived answer validity and accuracy, questions about their fallibility can again be raised (Research Question 3). On the basis of average responses to these items, the two groups can be regarded as comparable, even though there were some differences across prior knowledge, time-on-task, and information problem

solving behaviour. Paying particular attention to prior knowledge, the literature on judgements of learning would suggest that prior knowledge affects both confidence and accuracy (Toth, Daniels, & Solinger, 2011). In light of the current findings, this is not supported as the regression models using confidence judgements as outcome variables were not found to be appropriate. Future research is warranted to then explore why in the current instance the association between prior knowledge and judgements of learning was not supported. It may, as iterated by Winne and Jamieson-Noel (2002), be a case of items designed to gain an understanding of how learners perceive their achievement being biased. This is demonstrated in the current work as the data showed there to be no association between information problem solving behaviour, prior knowledge, or motivations and perceptions of achievement. It could, therefore, be implied that those who may not have effectively regulated their behaviour during the information problem solving task did not have a realistic perception of their outputs. Future work should then seek to identify ways to feed details about information problem solving behaviour back to students as a way of conveying an accurate representation of their learning process (Pardo et al., 2019; Winne, 2019).

Despite being a fundamental skill in both education and work-place domains (Brand-Gruwel et al., 2009; Winne, Vytasek, et al., 2017), many people experience problems associated with information problem solving (Walraven et al., 2008). Based on this premise, the current work sought to leverage the utility of concept maps, which provide a structured overview that offsets risks of confusion (Chen & Macredie, 2010; Minetou et al., 2008) and support comprehension of a topic (Nesbit & Adesope, 2006; Patterson, 2001). As shown by the results, strategies that invoked the use of the concept map varied very little between the high and low engagement groups, with only time-on-task being a meaningful difference. Prior literature would also suggest that individuals with both low and high prior knowledge would benefit from concept maps (Amadieu et al., 2009; Chen & Macredie, 2010; Minetou et al., 2008). Those within the High Engagement group were found to have higher prior knowledge overall, which would align with the expectations of concept maps increasing focus for these types of students (Amadieu et al., 2009). Even so, the findings alone cannot be used to understand if and how the concept map benefited students with high prior knowledge, only that there was an association with prolonged use of this particular tool.

4.1 Implications

Collecting fine-grained traces of information problem solving behaviour should be motivated by a view of providing actionable feedback (Gašević et al., 2015; Winne, 2019). To this end, the current findings could be used to provide learners with an accurate representation of their behaviour, which would overcome the fallibility of solely relying upon perceptions (Winne & Jamieson-Noel, 2002). For example, the visualisation of actions performed by the High Engagement group could be used to illustrate how those who were more successful dedicated a greater amount of time to the task and sought to gain a deeper understanding of the topic. These statements can be justified by the greater number of actions related to exploring links in a concept map and from a search tool, but also from their time-on-task measures. As stated by Winne, this information can then give a learner a better understanding of what strategies they previously enacted, but also what they could do differently in the future. The benefits of regulation feedback have been illustrated in the work of Timmers, Walraven, and Veldkamp (2015), where learners were encouraged to evaluate their performance. Results showed learners to engage in a greater number of information problem solving behaviours following feedback (Timmers et al., 2015).

As for the High Engagement group, their information problem solving strategy predominately consisted of browsing links, as was the case with the Low Engagement group (Brand-Gruwel et al., 2009). This is only one of three commonly cited search strategies (Brand-Gruwel et al., 2009; Lazonder, Biemans, & Wopereis, 2000), with the remaining two being utilisation of a search engine and typing a web address. Typing out web addresses was not permitted in the study, but querying a search engine was; occurrences of this strategy were exclusive to the latter stages of the study time. A possible reason could be that link dependency does require relatively little cognitive effort compared to search engine usage, where evaluating query appropriateness is a constant requirement (Thatcher, 2008). Traces obtained from the current work could then become important here as they illustrate a reluctance to initiate search strategies that could filter the search space. This could inform intervention developments that are focused on improving search strategy skills to offset possible dependencies on cycling through links.

Traditional approaches to understanding information problem solving behaviour have utilised self-report measures (Harding et al., 2019) or think

aloud protocols (Brand-Gruwel et al., 2005). In the case of self-reports, measures of attitudes and perceptions can be obtained that are not attainable through trace methodologies. Similarly, think alouds can provide researchers with a narrative of a respondent's thoughts during a task (Albers, 2015). For the purpose of exploring information problem solving, there are disadvantages to the application of either methodology. Self-reports may be constructed to provide a generalised view of the behaviour over multiple contexts (Winne & Perry, 2000) and repeated administrations of a scale may result in fatigue. Think alouds are cumbersome due to participants being required to verbalise their thoughts during the running of a study, which can be tiring (Van Someren, Barnard, & Sandberg, 1994). As shown here, trace methodologies can be used to circumvent some of these issues by providing an inexpensive way to collect information problem solving strategies. Moreover, alternate strategies taken by students could be identified through the application of data-mining techniques in the form of event sequence analysis and clustering. This is not meant to discount the utility of either self-report or think aloud methodologies as they can still offer insights not attainable from traces alone (e.g., student motivations).

4.2 Limitations

Following the recommendations of Winne (2019), the current work analysed granular traces of learner behaviour that occurred during an information problem solving task. Although it has provided an insight into the sequence of actions that students undertook, the level of granularity could go further. As described by Winne, further details about the information problem solving strategies enacted could be extracted by exploring the specific terms typed or links accessed during the information problem solving activity. This level of specificity would then provide a level of understanding not achieved here as it may be more indicative of a individual's approach (deep or surface) to learning.

A future endeavour that should be undertaken is to explore the validity of trace data being a proxy for educationally relevant constructs. Take motivation in the current work, this was measured using Elliot and Church's (1997) achievement goal orientation instrument and provides details that are indicative of students adopting a mastery or performance approach. The issue of administering a single instrument at one point in time is that it provides a static representation of motivation, which may not reflect reality. As

Martin et al. (2015) found, motivation does appear to show a high degree of variability over the course of a day. Therefore, it is reasonable to argue that student motivation within the current work could have fluctuated over the course of the task, but this would not have been identified. To resolve these issues of temporality, there is a need for future work to explore whether trace methodologies could be interchangeably used as valid measures of constructs such as motivation. Similarly, in the case of judgements of learning, where biases are a pertinent issue (Winne & Jamieson-Noel, 2002), there are grounds for exploring whether trace methodologies can objectively capture such perceptions (Jovanović et al., 2019; Zhou & Winne, 2012). Again, there is a need to explore the validity of such approaches, but it would circumvent any concerns of bias.

Even though the current work set out to explore the effects of various internal conditions on information problem solving strategies, there were measurement issues. In particular, the scales measuring need for cognition (Cacioppo et al., 1984) and perceived usefulness (Davis, 1989) were identified as being problematic. These issues could be attributed to the sample size used here ($n = 111$) or it may represent an issue with the scales themselves. The next steps should be to investigate whether there are inherent problems with the scales or if these issues can be rectified with the use of larger samples. Moreover, the measures of internal conditions was not exhaustive, with personality and epistemological beliefs not being considered (Winne & Hadwin, 1998). The personality construct of conscientiousness is of particular relevance here as it is associated with adopting a methodical and attentive approach to work (Perry, Hunter, Witt, & Harris, 2010). In the context of information problem solving, students being higher in conscientiousness may have spent more time exploring the search space and evaluating resources. As these variables were not measured, this will continue to be a gap within the literature. Thus, in conjunction with the need for larger sample sizes, future research research needs to encompass a greater number of variables that could be subsumed under internal conditions.

A further limitation of this work was the oversight to collect background details on students (e.g., demographics, prior academic performance, and experience). These are, in effect, conditions that may have attributed to how students approached the information problem solving activities (Winne, Vytasek, et al., 2017). Although prior-knowledge was measured, which provides a means of understanding the level of experience a student has with the domain area, there are additional caveats to consider. Take, for instance, the

subject students are studying, this could have associated effects on information problem solving skills, knowledge of the tools provided, and the ability to construct cohesive essays. Steps should be taken to explore the implications that these additional variables would have on the models presented.

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