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Measuring critical components of digital literacy and their relationships with learning

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ABSTRACT

The growing prominence of the Internet, and other digital environments, as educational tools requires research regarding learners' digital literacy. We argue that two critical aspects of digital literacy are the ability to effectively plan and monitor the efficacy of strategies used to search and manage the wealth of information available online, and the knowledge to appropriately vet and integrate those information sources. Therefore, digital literacy requires effective self-regulated learning (SRL) skills, and availing epistemic cognition (EC). Although numerous researchers and scholars have examined the role of SRL in online learning (e.g., Efklides, 2011; Lee & Tsai, 2010; Williams & Hellman, 2004; Winters, Greene, & Costich, 2008), there is a need for additional empirical research on how SRL and EC interact, and relate to learning in digital environments. In this study, we used a powerful, but little-used data collection methodology, think-aloud protocol (TAP) analysis, to investigate the relations among SRL, EC, and learning gains with 20 college students who studied vitamins on the Internet. We also contributed to the literature by exploring alternative techniques for preparing, analyzing, and representing these data, accounting for the strengths and challenges of TAPs. We found that, on average, participants did increase their understanding as a result of learning with the Internet, and that a data-driven approach to understanding relations among SRL, EC, and learning yielded the most powerful representation of these phenomena. Our study has implications for future research on digital literacy using TAPs, as well as the relative contribution of SRL and EC, as aspects of digital literacy, to online learning.

1. Introduction

Twenty-first century learning skills require the ability to use Internet technology. The prominent role the Internet plays in home and classroom lives demands careful attention to its link to student knowledge gains. One challenge facing learners trying to understand information from the Internet is its sheer volume of information, and the many ways that information is presented. The Internet, as a text, consists of multiple print, images, videos, and interactive simulations, all used to communicate and inform, with subsequent effects upon cognition (Collins & Halverson, 2009; Gee, 2007). While it is important to consider how Internet use affects students' different cognitive processes (Reinking, 2005), it is equally important to consider how different cognitive processes influence how students engage with, and learn from, the Internet (e.g., Strømsø & Bråten, 2010). The term "digital literacy" refers to the cognitive processes that individuals partake in during the utilization of computer-based, multimodal information (Goldman et al., 2010; Mayer, 2005; Schnotz, 2005; Sweller, 2005). Unfortunately, despite conventional wisdom that students are "digital natives" (Prensky, 2001) who are literate, and even proliferate, Internet users (Palfrey & Gasser, 2008), research evidence indicates that many students struggle to find, understand, vet, and integrate information from the Internet (Bennett, Maton, & Kervin, 2008; Coiro, Knobel, Lankshear, & Leu, 2008; Nasah, DaCosta, Kinsell, & Seok, 2010; Selwyn, 2009). These learners lack digital literacy skills, and their uncritical consumption is dangerous given the often-misleading nature of online information (e.g., Eysenbach, Powell, Kuss, & Sa, 2002).

Given that the integration of online resources into education shows no sign of abating (Nuckles & Bromme, 2002), students need to improve their digital literacy skills. Many students who use the Internet do not engage in a thoughtful approach to searching and often become

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0360-1315/

overwhelmed by the myriad of online resources (Shapiro & Niederhauser, 2004). Self-regulated learning (SRL; Winne & Hadwin, 2008; Zimmerman, 2000) skills, inclusive of making effective plans, and monitoring and controlling these plans, as well as the strategies used to enact those plans and the learning that results (Azevedo & Jacobson, 2008), are likely to be critical components of digital literacy. However, even those students who effectively self-regulate their learning often lack the adaptive beliefs and critical thinking skills, i.e., epistemic cognition (EC; Chinn, Buckland, & Samarapungavan, 2011; Greene, Azevedo, & Torney-Purta, 2008; Hofer & Pintrich, 1997; Muis, 2007) essential to identifying trustworthy online sources of information, avoiding biased websites, and integrating divergent thinking into actionable knowledge (Clark & Slotta, 2000; Mason, Ariasi, & Boldrin, 2011; Mason, Boldrin, & Ariasi, 2010). Therefore, given the vast amount of information available online, and the great variance in its quality, both SRL and EC are critical components of 21st century digital literacy, and both require further research.

While more research is needed to understand what students do and think while learning online, concerns over measurement issues are becoming increasingly salient in both the SRL (e.g. Veenman, 2005; Winne & Perry, 2000) and EC (e.g. Greene & Yu, 2014; Hofer & Sinatra, 2010) literature. While self-report questionnaires dominate the research literature in SRL and EC, they have notable psychometric problems (Clarebout, Elen, Luyten, & Bamps, 2001; DeBacker, Crowson, Beesley, Thoma, & Hestevold, 2008; Veenman, 2007; Winne & Jamieson-Noel, 2002). There is growing interest in using think-aloud protocols (TAPs: Ericsson & Simon, 1993; Greene, Robertson, & Costa, 2011) to capture SRL and EC as they occur (Azevedo, 2005; Greene & Azevedo, 2009; Hofer, 2004; Mason et al., 2010, 2011). To our knowledge, there have been no previous attempts to utilize TAPs to capture both SRL and EC in the same study.

Although a promising form of data collection, a major disadvantage to using TAPs is the very high resource demand associated with collecting, preparing, and analyzing the data (Greene, Costa, et al., 2011; Greene, Robertson, & Costa, 2011). These resource demands result in small sample sizes relative to the large number of SRL and EC processes that could be coded from TAP data. Greene and Azevedo (2009) proposed aggregating what they called “micro-level” SRL TAP data into “macro-level” SRL variables such as planning, monitoring, and strategy use. Such methods have not been attempted with EC data, and it is not clear whether simple aggregations of micro-level data produce macro-level variables with optimal specificity and predictive utility for a particular context, sample, or learning task (Greene, Dellinger, Binbasaran Tuysuzoglu, & Costa, 2013).

In this study we examined how both SRL and EC related to learning gains when college students used the Internet to learn about a public health and science topic: vitamins. Understanding the concerns about self-report measures, we chose to utilize TAPs to collect SRL and EC data. However, given resource and power concerns, we explored alternate approaches for preparing, analyzing, and representing the data, taking into account both the advantages and challenges associated with TAP data collection as well as the contextualized nature of SRL and EC. We believe that our analyses make contributions to the literature regarding how critical aspects of digital literacy, i.e., SRL and EC, relate to learning, while also introducing a novel and generative way to gather and analyze these data, i.e., TAPs.

1.1. Theoretical background and rationale

1.1.1. Traditional definitions of digital literacy

Digital media encompasses more than words and language as forms of communication by including images, symbols, video, music and animation (Collins & Halverson, 2009; Gee, 2007). Indeed, when addressing complex topics, such as science, the Internet can be an advantageous resource because of its facility at presenting multiple representations of phenomena that can be used to promote positive public understanding of science (Sinatra & Chinn, 2012). Jacobson and Archodidou (2000) cited several advantages to learning about complex topics on the Internet, including hyperlinks that can non-linearly present multiple representations of information that users have the ability to control. The multimodal, dynamic, and interactive nature of Internet learning can foster the declarative, procedural and conceptual knowledge (Schraw, 2006) necessary for students to transfer their knowledge to problems in the real world (Roth, 1990).

Digital literacy however, requires of the reader not just the recognition of these multiple forms of representation, but an integrated understanding of these representations (Gee, 2007). Some researchers have equated digital literacy with search literacy, or searching for information online and information literacy (Hockley, 2012; Ng, 2012). For example, cognitive overload and disorientation are two primary reasons why students struggle to search the Internet effectively (Gerjets, Scheiter, & Schuh, 2008). Yet, given the varying veracity of information online, digital literacy must include not only the ability to effectively search for information, but also to vet and integrate that information while monitoring progress toward learning goals (Bråten, Britt, Strømsø, & Rouet, 2011).

We believe that current definitions of digital literacy do not sufficiently emphasize the essential cognitive and metacognitive processes needed to learn effectively from multiple representations of content. Instead, we view digital literacy as critically inclusive of searching, vetting and integrating information into the meaning-making process during online learning. Students require effective SRL skills (Azevedo & Jacobson, 2008; Greene & Azevedo, 2009; Posner & Rothbart, 2005; Sitzmann & Ely, 2011; Zimmerman, 2000) in conjunction with availing EC (Bråten et al., 2011; Greene, Muis, & Pieschl, 2010; Mason et al., 2011) to learn with digital sources like the Internet.

1.1.2. Self-regulated learning

Researchers have found that students' academic success often depends upon their ability to self-regulate their learning (Winne & Hadwin, 2008; Zimmerman, 2000; Zimmerman & Labuhn. 2012). Numerous models of SRL exist, but most present a common conceptualization of learners as active constructors of knowledge who loosely follow a set of procedures before, during, and after learning (Pintrich, 2000). These procedures include defining tasks and setting goals, making plans, enacting strategies to achieve the goals, and monitoring learning progress toward those goals, among other activities. When learners determine that they are making insufficient progress, they enact control, and make changes to their strategies, and in certain situations, their goals, plans, or task definitions (Bjork, Dunlosky, & Kornell, 2013). Ideally, after completing a task, learners reflect upon their performance and make any necessary changes to their knowledge and beliefs regarding learning, so that future tasks can be accomplished more efficiently and effectively (Winne, 2001; Zimmerman & Labuhn, 2012). Motivation and self-beliefs are purported to strongly influence the degree to which learners are willing to engage in the key aspects of SRL, including planning, monitoring, and strategy use (Greene & Azevedo, 2007; Muis, 2007; Pintrich, 2000; Winne & Hadwin, 2008; Zimmerman, 2000).

SRL skills have become increasingly pertinent even for those who are not full-time students, as technological avenues for information acquisition, across multiple knowledge domains (Alexander, Dinsmore, Parkinson, & Winters, 2011), increasingly require independent learning skills. SRL skills are therefore paramount in a world of technologies capable of presenting vast amounts of information regarding complex topics in multiple representations (Azevedo, 2005; Greene & Azevedo, 2009; Shapiro & Niederhauser, 2004). SRL and its role in online learning have become increasingly prominent in research and scholarship (e.g., Efklides, 2011; Lee & Tsai, 2010; Williams & Hellman, 2004; Winters, Greene, & Costich, 2008). The Internet embodies the modern day circumstance: a wealth of information exists, but a simple Google search can retrieve literally thousands of sites, with varying degrees of relevance, accuracy, and comprehensibility. Internet users become quickly overwhelmed if they cannot effectively self-regulate their learning (e.g., make a plan, monitor how they construct their own representations of information, etc; see Appendix A for the list of all SRL processes identified in this study).

1.1.3. Epistemic cognition

EC encompasses an array of cognitive phenomena that guide and facilitate the acquisition and reification of knowledge (Chinn et al., 2011; Greene et al., 2008), helping to create the conditions within which adaptive learning occurs (Bromme, Pieschl, & Stahl, 2010; Pieschl et al., 2009) while also increasing the likelihood of higher quality digital learning (Tu, Shih, & Tsai, 2008). For example, EC includes the evaluation of sources of knowledge claims and the reconciliation of conflicting claims by multiple resources (Bråten et al., 2011). As another example, it is often considered most helpful to learning when one believes knowledge is complex rather than simple (Schommer, 1990), i.e., defining learning as a congealing of connectable information into a coherent whole as opposed to the memorization of discrete information having little to no relationship to each other.

Many researchers within the field of EC continue to focus upon learners' beliefs about the nature of knowledge (e.g., its simplicity and certainty) and the nature of knowing (e.g., the source of a knowledge claim, and its justification) (Hofer & Pintrich, 1997). However, recent work in the field has placed an emphasis on a broader set of cognitive processes including the multiple kinds of justifications that learners use (Greene et al., 2008) and aspects of learners' goals for learning (i.e., epistemic aims, Chinn et al., 2011). We included these perspectives in our work by organizing them into the following categories: nature of knowledge, justification, source evaluation, and epistemic aims (see Appendix B for the list of all EC processes identified in this study).

1.1.4. Integrating self-regulated learning and epistemic cognition

Relations between SRL and EC have been posited for almost 20 years (e.g., Hofer & Pintrich, 1997). Among other relationships, EC is purported to influence the standards that learners set (Muis, 2007) throughout all phases of SRL (Greene, Bolick, & Robertson, 2010; Greene, Costa, Robertson, Pan, & Deekens, 2010; Greene, Muis, et al., 2010) and shape the internal conditions for learning that allow for calibration to new tasks (Bromme et al., 2010). In addition, SRL is theorized to have a reciprocal effect upon EC (Muis, 2007). Therefore, given recent interest in how SRL and EC might mutually interact to influence learning in physical and digital environments (e.g., Bromme et al., 2010; Greene, Bolick, et al., 2010; Greene, Costa, et al., 2010; Greene, Muis, et al., 2010; Mason & Bromme, 2010; Strømsø & Bråten, 2010), we wished to examine relations among these cognitive and metacognitive phenomena and learning outcomes.

1.1.5. Measuring SRL and EC

Much of the research on SRL, including applications to digital literacy, has involved self-report measures that have been shown to be inaccurate and untrustworthy (Winne & Jamieson-Noel, 2002; Winne & Perry, 2000). Likewise, much of the empirical research on EC has been built on self-report surveys, but these measures have shown very poor psychometric qualities (e.g., DeBacker et al., 2008). Therefore, despite compelling conceptual models of these relations (e.g., Muis, 2007), the field has been stymied by problems with the predominant form of measurement in both fields, self-report (Greene, Bolick, et al., 2010; Greene, Costa, et al., 2010; Greene, Muis, et al., 2010).

Promising recent work regarding how learners' EC relates to their use of computers has moved beyond self-report to other types of measures (e.g., Bråten et al., 2011; Hofer, 2004; Mason et al., 2011), as it has in the literature on SRL (e.g., Azevedo, 2005; Greene, Hutchison, Costa, & Crompton, 2012; Moos & Azevedo, 2008; Veenman, 2005, 2007). TAPs, which involve participants verbalizing but not explaining their thinking as they engage in a task (Ericsson & Simon, 1993), provide far more accurate measures of SRL, with stronger predictive relations with learning, than self-report measures (Veenman, 2005, 2007). This is because phenomena that are metacognitive in nature (e.g., SRL) and deeply tacit (e.g. EC; Hofer, 2006) are difficult to self-report when investigated retrospectively and in reference to a global domain, rather than a very specific task, which is how surveys typically prompt their respondents (Winne & Perry, 2000). Further, TAP data are fine-grain and in situ, compared to self-report data. Despite the increasing use of TAPs in the literature, we are not aware of a study that has used TAPs to capture both SRL and EC from the same participants.

We built off of prominent theoretical work (Azevedo, 2005; Winne & Hadwin, 2008; Zimmerman, 2000) to identify the SRL processes necessary to successfully manage the vast amount of information found online. We used a scheme developed by Azevedo, Greene, and colleagues (e.g., Azevedo & Cromley, 2004; Greene & Azevedo, 2009) to code TAPs for indications of SRL processing. TAPs can be transcribed and divided into codable segments of text that serve as evidence of learners' cognitive and metacognitive processing. For example, when a learner states, "I don't understand that" this verbalization segment can be coded as a *judgment of learning* (cf. Azevedo & Cromley, 2004). Numerous researchers have introduced valence to SRL TAP coding schemes, by distinguishing between positive (e.g., "I understand that") and negative (e.g., "I don't understand that") forms of a codes. We included valence for relevant codes (see Appendix A) and investigated Azevedo and colleagues' techniques for analyzing these data (see Section 1.2.1). In addition, we expanded Azevedo and colleagues' SRL TAP coding scheme by adding 15 codes (see Appendix B) derived from EC research (Chinn et al., 2011; Greene et al., 2008; Hofer, 2006). As an example, "This website seems pretty reliable" can be coded as a *source evaluation positive*. We felt that these data would capture learners' SRL and EC within a digital environment. However, TAPs are resource-intensive to gather, and produce a vast amount of data, necessitating an exploration of alternative methods of best preparing, analyzing, and representing those data.

1.2. Analyzing think-aloud data to understand digital literacy phenomena

1.2.1. Approach #1: full aggregation

Greene and Azevedo (2009) have argued that the coded TAP behaviors, while helpful, problematically vary in kind and frequency from individual to individual. They have aggregated what they call coded micro-level SRL process TAP data (e.g., judgments of learning) into macro-level SRL variables (e.g., monitoring) that they believe better capture relevant variance regarding the degree to which learners self-regulate their engagement with complex materials. Further, Greene and Azevedo have argued that macro-level analyses better control for idiosyncratic differences in the specific actions that learners choose to enact (e.g., taking notes versus summarizing). Ultimately, according to Greene and Azevedo (2009; Greene et al., 2013), it is helpful to analyze the degree to which participants are engaging in macro-level SRL processing such as planning, monitoring, and strategy use, as opposed to focusing on whether learners are enacting particular examples of those macro-level SRL processes (i.e., micro-level SRL processes such as setting a subgoal versus accessing prior knowledge). Numerous researchers have successfully used these methods to demonstrate relations between learning with computers and the quality of SRL processing (cf., Greene, Bolick, et al., 2010; Greene, Costa, et al., 2010). For our study, we investigated macro-level SRL codes, and we aggregated our micro-level EC codes into macro-level ones as well (see Appendix A for each code's micro- and macro-level designation).

While TAPs have been lauded for their ability to provide high-quality data for SRL and EC (e.g. Greene, Muis, et al., 2010; Hofer, 2004), the data collection effort is extremely labor intensive, posing a formidable constraint to researchers hoping to share meaningful findings backed by strong statistical support (Greene, Costa, et al., 2011; Greene, Robertson, et al., 2011). Unlike self-report measures, which can be administered to increasingly large numbers of respondents while incurring relatively little added burden with the addition of each participant, TAPs bare a heavy resource load for each individual participant involved in a study. For this study, a minimum of seven researcher hours per study participant was required from the point of data collection to the point at which raw data were converted into a form amenable to quantitative analysis. The resource demands of using TAPs to measure SRL and EC often lead to relatively small sample sizes that affect statistical power.

Although we decided to explore Greene and Azevedo's (2009) method for data analysis that aggregated all micro-level SRL codes into their macro-level variables, we also thought it likely that within any particular context, only certain micro-level SRL, or EC, behaviors are associated with adaptive and availing learning (Greene et al., 2013). In effect, summing all micro-level codes may lead to diluted macro-level variables because less influential micro-level codes may add noise that can drown out an otherwise noticeable signal. Given that power issues were a concern, we explored the possibility of an alternative approach to analyzing the data that we believed might lead to stronger macro-level variables.

1.2.2. Approach #2: data-driven aggregation

Given the potential problems with simply summing all micro-level processes into macro-level variables, we sought to narrow our focus upon those micro-level processes that proved to be most related to learning. This alternative approach, first suggested by Greene and colleagues (2013), was more data-driven in that it eliminated from analytical consideration the micro-level processes that did not demonstrate strong bivariate associations with learning gain. In addition, we decided to remove the boundaries among all of the sub-dimensions within SRL and EC. We chose to examine the correlation between each micro-level code and learning gains, and group them into positive and negative relations. For example, using data-driven aggregation techniques, if judgments of learning and interest both had positive relations with learning gains, then we could combine them into a single macro-level SRL variable (i.e., "positive SRL"). To determine which micro-level SRL codes to aggregate, we examined the range of correlation magnitudes between each code and learning gain, and investigated the predictive validity of macro-level SRL variables with cutlines at various thresholds (e.g., all micro-level SRL codes with an r equal to .1 or greater, .15 or greater, etc.). We utilized the same process for the EC codes. Finally, we examined the predictive validity of various combinations of macro-level variables through regression analysis.

To summarize, in an effort to negotiate the TAP affordance of capturing large amounts of high quality data as well as the disadvantages of statistical restrictions due to resource demands, we investigated two different ways of analyzing SRL and EC process variables. The first was an approach developed by Greene and Azevedo (2009) that organized all micro-level cognitive variables into theoretically delineated sub-dimensions of SRL and EC (See Appendices A and B, macro-level process). The second, more data-driven approach selected and grouped only certain micro-level processes based upon the degree of their association with learning gains, allowing statistical relationships to guide analysis and provide new insights into the contextualized nature of learning and digital literacy (Greene et al., 2013).

1.3. Overview of the current study

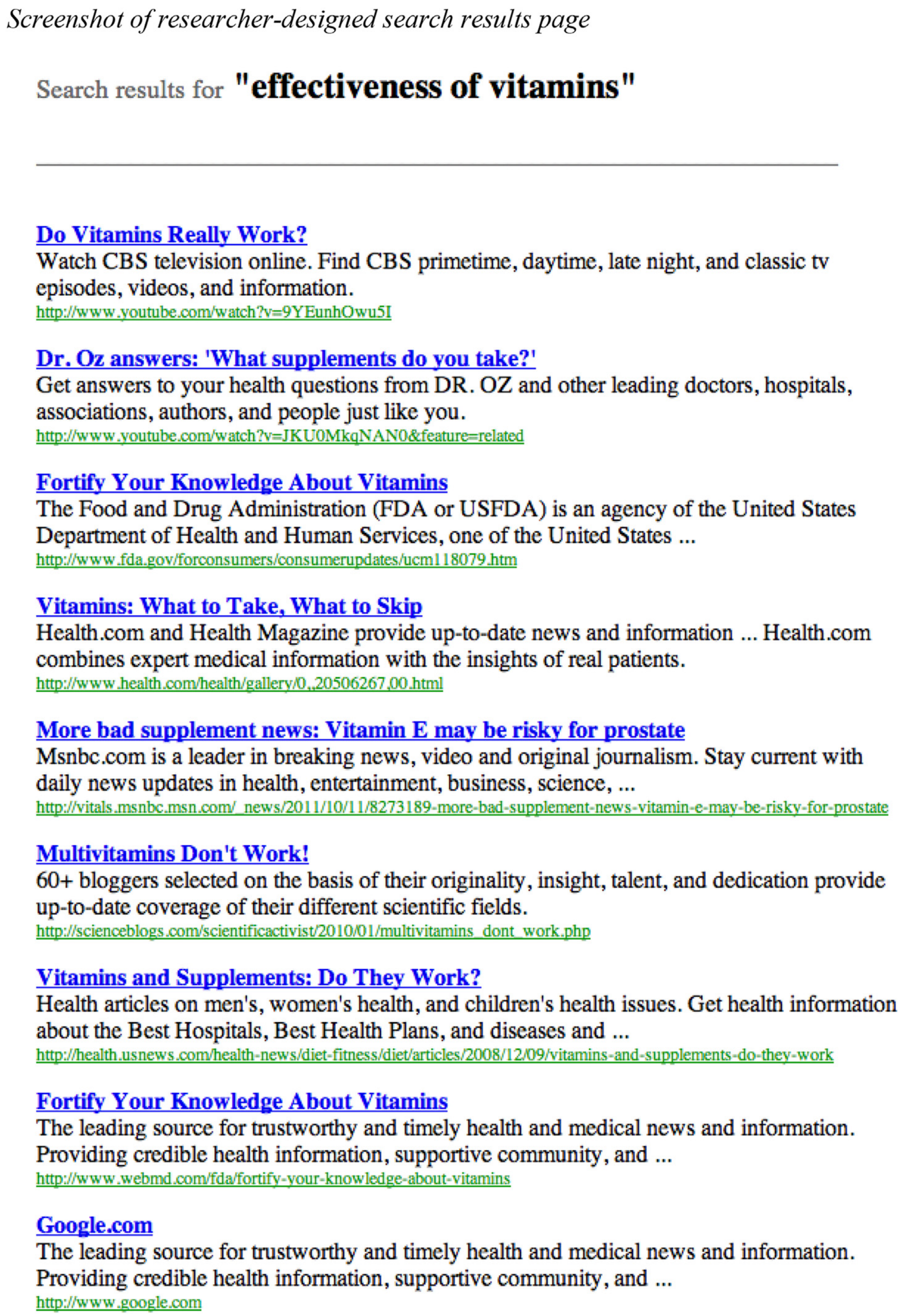
In this study, we wished to examine how critical aspects of digital literacy (i.e., SRL and EC) related to college students' learning gains while using the Internet to investigate an everyday public health and science topic. We expanded upon previous research by using TAP methodology to capture both SRL and EC, and to test their relations with learning gains. However, resource demands and power issues posed serious challenges that required the investigation of alternative methodologies for preparing, analyzing, and representing our data. We believe that the results of our work inform both the substantive literature on digital literacy as well as provide guidance regarding how TAP methodologies can be used for future research in this area. We had three research questions:

RQ1: Does participants' knowledge of vitamins and health improve from pretest to posttest, after using the Internet to learn?
RQ2: To what degree do participants' SRL and EC processing predict learning gains?
RQ3: Which method of computing macro-level SRL and EC variables best captures relations with learning gains?

2. Method

2.1. Participants

At a large university in the southeastern United States, 20 students (7 women) from an undergraduate elective course in education volunteered to participate in a 90-min study on student beliefs and learning. As an incentive, they received extra credit in their course. The participants' mean age was 20.15 ($SD = 1.79$). 15 of the students were in their first or second year of college. While seven students had not yet decided their major, the rest of the participants represented a diversity of majors.



Screenshot of researcher-designed search results page

Search results for **"effectiveness of vitamins"**

Do Vitamins Really Work?
Watch CBS television online. Find CBS primetime, daytime, late night, and classic tv episodes, videos, and information.
http://www.youtube.com/watch?v=9YEunhOwu5I

Dr. Oz answers: 'What supplements do you take?'
Get answers to your health questions from DR. OZ and other leading doctors, hospitals, associations, authors, and people just like you.
http://www.youtube.com/watch?v=JKU0MkqNAN0&feature=related

Fortify Your Knowledge About Vitamins
The Food and Drug Administration (FDA or USFDA) is an agency of the United States Department of Health and Human Services, one of the United States ...
http://www.fda.gov/forconsumers/consumerupdates/ucm118079.htm

Vitamins: What to Take, What to Skip
Health.com and Health Magazine provide up-to-date news and information ... Health.com combines expert medical information with the insights of real patients.
http://www.health.com/health/gallery/0,,20506267,00.html

More bad supplement news: Vitamin E may be risky for prostate
Msnbc.com is a leader in breaking news, video and original journalism. Stay current with daily news updates in health, entertainment, business, science, ...
http://vitals.msnbc.msn.com/_news/2011/10/11/8273189-more-bad-supplement-news-vitamin-e-may-be-risky-for-prostate

Multivitamins Don't Work!
60+ bloggers selected on the basis of their originality, insight, talent, and dedication provide up-to-date coverage of their different scientific fields.
http://scienceblogs.com/scientificactivist/2010/01/multivitamins_dont_work.php

Vitamins and Supplements: Do They Work?
Health articles on men's, women's health, and children's health issues. Get health information about the Best Hospitals, Best Health Plans, and diseases and ...
http://health.usnews.com/health-news/diet-fitness/diet/articles/2008/12/09/vitamins-and-supplements-do-they-work

Fortify Your Knowledge About Vitamins
The leading source for trustworthy and timely health and medical news and information. Providing credible health information, supportive community, and ...
http://www.webmd.com/fda/fortify-your-knowledge-about-vitamins

Google.com
The leading source for trustworthy and timely health and medical news and information. Providing credible health information, supportive community, and ...
http://www.google.com

Fig. 1. Screenshot of researcher-designed search results page.

2.2. Procedure

Each 90-min session was held in a research laboratory, with one participant and one researcher present. After greeting participants, the researcher followed standard ethical protocols for human subjects research and gave a step-by-step overview of the entire session. The participants answered a demographic questionnaire (see Section 2.3.1) and then had 20 min to complete a knowledge pretest (see Section 2.3.2).

In preparation for the think-aloud activity, the researcher read the learning task aloud, which stated: "Imagine that you have been asked to write a 5-page paper for an undergraduate elective class in public health on whether taking a daily vitamin pill is helpful for normal, healthy adults. You decide to consult sources on the Internet. We have provided you with a list of pages that came up after your first search, which you may consult if you wish. You are also free to consult any other webpages you wish." Then the researcher explained the TAP process in detail. Instructions were given to verbalize everything that the participants were thinking or reading during the learning task, as they navigated the Internet. Following this, participants were asked to practice thinking aloud for roughly 2 min on a website about animals,

Table 1
Pretest and posttest scoring Rubric.

Subscale	1 Point	2 Points	3 Points
Vitamins	• Vitamin supplements help a body stay healthy in the case of healthy adults • Vitamins can give benefits to people (e.g. energy)	• The body does not process all nutrients in the same way • The body's vitamin requirements are different from vitamin to vitamin • Vitamins exist in the body at different levels in each person	• There are reasons why "the body does not process all nutrients the same" (e.g. soluble and fat soluble, Vitamin D acquisition via exposure to sunlight) • Specific treatment/attention of particular vitamins in relation to a particular person (this was added)
Mechanism	• Nutrients can come from food & vitamin supplements • The body has minimum requirements for nutrients to be healthy	• Food is the better source of nutrients, not vitamin supplements • Exceeding daily recommended levels of nutrients is not necessarily desirable	
People	• Vitamin supplements are good/bad for everyone	• Different kinds of people, respond to vitamins (or vitamin supplements) differently	• Vitamin supplements are good for older people who lack exposure to sunlight
Interaction	• The body needs nutrients to function well.	• If a person is not getting enough vitamins from food, the body suffers. The person should take vitamin supplements to compensate.	
Other aspects (e.g. negative effects)		• Too much of a vitamin could be bad for you	

a site similar in structure to those to be encountered during the learning task, but with different content. When it was clear that participants understood how to verbalize their thoughts and actions for the purpose of the think-aloud, the researcher stopped the practice session.

Participants were given additional details before beginning the learning session. First, the learning task was reread aloud and a written version of it was placed next to the computer monitor, where it stayed for the duration of the 30 min. Participants were allowed full access to the Internet during the 30-min learning task. They were told that their searches could go anywhere on the Internet, beginning with a webpage designed by the researchers to resemble the appearance of an initial search result for "effectiveness of vitamins" (see Fig. 1). One of these links was to the "google.com" search engine. Aside from this initial search results page, the session was devoid of any suggestions that might direct Internet activity, to bolster ecological validity. Participants were allowed to take notes, but were told that notes could not be used on the posttest that would follow. The learning sessions were both audio and video recorded. While the researcher was not allowed to answer any participant questions regarding the task or its content, prompts were given at 20, 10, 5, and 2 min to notify the participants of the time remaining in the session.

After starting the recording devices, the timer was started and the participants were instructed to begin the learning task. The timer was visible to the participants. At the end of 30 min, the computer screen was turned off and all task-related stimuli were removed. Then the participants were given the posttest, which was identical to the pretest. Participants had 20 min to finish it, with no access to notes or instructional materials. Last, participants were asked if they experienced any difficulties during the learning task and if they had any comments regarding the overall experience that may be helpful to the researchers.

2.3. Data sources

2.3.1. Demographic questionnaire

A short survey asked for information on age, sex, year in school, major, and GPA.

2.3.2. Measuring knowledge and learning

The pretest and the posttest were identical, but participants were not told this until after completing the learning task (i.e., immediately prior to taking the posttest). Participants had 20 min to handwrite a response to the following prompt: "Imagine that you are taking a final exam in a public health elective course. Please respond to this question in the space below: 'If your friend, who is a normal healthy adult, asked you whether he or she should start taking a daily vitamin pill, what would you tell this person to do, and why? Be sure to include any relevant evidence that supports your advice.'" No further information or assistance was given. No participant needed more than the 20 min allotted for either pretest or posttest. Most participants finished writing within the first 15 min for both the pretest and the posttest.

A scoring system to assess vitamin conceptual knowledge was designed by the researchers with the assistance of pharmaceutical and nutrition professionals over six meetings and 5 h of consultation (see Table 1). An ideal essay response included expressed understandings of concepts such as the difference between water-soluble and fat-soluble vitamins, variability in nutrient needs based upon individual person characteristics (e.g. age, pregnancy), and how vitamin supplements may actually cause harm to the body. Participant scores ranged from 1 to 12, indicating increasing levels of conceptual understanding. The first and second authors individually scored each pretest and posttest, and resolved any differences via consultation. There were no disagreements.

2.3.3. Think-aloud verbalizations and coding micro-level processes

Participants' continuous verbalizations during the 30-min learning task provided the raw data for this SRL and EC aspects of this study. The participants' TAPs were transcribed using audio and video recordings. One of the two first authors divided each transcript into codable segments, which were then each assigned a micro-level SRL or EC process. Then, the transcripts were exchanged and recoded by the other researcher. Researchers met to reconcile differences, resulting in no disagreements.

The coding scheme used was originally developed by Azevedo and Cromley (2004) and applied to the think-aloud material captured during the learning task. This coding scheme has yielded data that have been highly reliable and predictive of learning (Azevedo, 2005; Greene, Costa, et al., 2010). Constructs delineated by EC researchers (Chinn et al., 2011; Greene et al., 2008; Hofer & Pintrich, 1997) were incorporated into the TAP data coding methodology. The resulting SRL and EC coding scheme totaled 47 codes that represented different micro-level SRL (i.e., 32 of the 47 codes) and EC (i.e., 15 of the 47 codes) processes, including setting sub-goals, judgments of learning, taking notes, stating that knowledge is simple or certain, making justifications, evaluating sources, and describing their epistemic aims. Some of these categories had valences (e.g., source evaluation: SE+ and SE−) increasing the total number of micro-level SRL and EC coding categories to 82. Regarding valence for justification codes, the ± distinction indicated whether the form of the justification (perception, testimony, rationality, etc.) either supported (+) treating the claim qua knowledge or refuted (−) the claim as knowledge. Appendices A and B give code categories and descriptions. Two additional codes were tutor-initiated time monitoring and no code. The former was enacted four times for each participant by the researcher and the latter was reserved for participant verbalizations that did not fit the a priori coding scheme. Direct reading of text and audio input from video was transcribed but uncoded unless it constituted re-reading.

2.4. Statistical analyses

A statistical analysis of pretest and posttest scores provided evidence regarding our first research question. Then, participant scores were represented as learning gains by calculating the difference between posttest and pretest scores for each individual, and subsequently used in the analyses for our last two research questions involving the TAP data. Research questions 2 and 3 were exploratory, and compared the adequacy and fidelity of different approaches to preparing, analyzing, and representing the TAP data.

Two approaches (i.e., full and data-driven aggregation; see Section 1.2) were taken for the organization of micro-level categories and statistical analyses. Micro-level codes were aggregated into macro-level variables, to address power issues and to account for inter-individual differences that might affect specific SRL and EC processing (cf., Greene & Azevedo, 2009; Greene et al., 2013). Macro-level variables were then used in subsequent bivariate correlation and regression analyses.

The “full aggregation” approach to computing macro-level variables was based upon the methods used by Greene and Azevedo (2009), and included only those micro-level SRL variables that were previously posited to have significant relations with learning, resulting in the exclusion of *control video* and *selecting a new information source* from the strategy use variable. This method of grouping the micro-processes was driven by theoretical and empirical literature regarding SRL processes that influence learning. Specifically, the three categories used were: planning, monitoring, strategy use. We took the same approach for our EC variables: beliefs about the nature of knowledge, justification, source evaluation, and epistemic aims.

The second approach to analysis, i.e., “data-driven aggregation” began by scrutinizing the correlations of micro-level process frequencies with learning gains. As with the first approach, *control video* and *selecting a new information source* were excluded from consideration. The new macro-variables for this approach were identified as: positively correlated SRL micro-variables, positively correlated EC micro-variables, negatively correlated SRL micro-variables, and negatively correlated EC micro-variables. To warrant inclusion in a macro-variable, micro-variables must have met a minimal correlation cutline based upon their magnitude of relationship with learning gain. We investigated three correlation cutlines: ±.1, ±.15, and ±.2. Micro-level processes with a magnitude of correlation less than .1 were not included in any analyses in this second approach to analysis. For each cutline, we regressed learning gain on the macro-level variables that resulted. Then, we compared both statistical and practical significance at each cutline, to determine the optimum set of macro-level predictors.

3. Results

Our first research question was posed to investigate whether participants, on average, gained in their understanding of vitamins from pretest to posttest. Our second and third research questions involve analyses of the relations among measures of digital literacy (i.e., SRL and EC) and learning gains.

3.1. Knowledge gains

Pretest ($M = 3.00$, $SD = 2.32$) and posttest data ($M = 5.55$, $SD = 2.74$) were normally distributed. Learning gain scores based on pretest to posttest ranged from −1 to 7 ($M = 2.55$, $SD = 2.44$). However, given the relatively low sample size, we analyzed our data using both parametric and non-parametric tests. A paired-samples *t*-test showed a statistically significant gain from pretest to posttest [$t(19) = 4.677$, $p < .0001$, Cohen's $d = 1.059$]. A Wilcoxon Signed Ranks Test also resulted in statistical significance ($Z = 3.402$, $p < .001$). Thus, on average, participants' responses to whether normal, healthy adults should take vitamins improved from pretest to posttest following a 30-min online learning session. These results laid the groundwork for further analysis to address our second and third research questions.

3.2. Exploring relations between measures of digital literacy and learning

Our second and third research questions required an investigation of multiple analysis techniques. These analysis techniques differed in terms of how macro-level SRL and EC process variables were created. Comparisons between techniques were necessary to determine the best representation of our data.

3.2.1. Approach #1: full aggregation

The first method of analysis followed Greene and Azevedo's (2009) recommendation of summing all SRL and EC micro-level processes into their macro-level variables. Table 2 provides descriptive statistics for the theoretically formed macro-level variables as well as the summed total of all SRL and EC macro-level variables (i.e., TotalSRL and TotalEC). As was expected, SRL process behaviors were much more

Table 2
Descriptive statistics for macro-level SRL and EC variables and totals – approach#1: full aggregation.

Variable	Mean (SD)	Range	Skewness (SE)	Kurtosis (SE)
Planning	6.50(4.73)	0–15	.478(.512)	−.865(.992)
Monitoring	18.7(11.08)	2–46	.564(.512)	.676(.992)
Strategy Use	36.20(14.65)	9–60	−.311(.512)	−.551(.992)
TotalSRL	61.40(25.47)	11–116	−.105(.512)	.464(.992)
Nature of Knowledge	.15(.37)	0–1	2.12(.51)	2.78(.99)
Justification	1.55(1.79)	0–6	1.19(.51)	.82(.99)
Source Evaluation	4.20(2.98)	0–13	1.94(.51)	5.50(.99)
Epistemic Aims	.10(.31)	0–1	2.89(.51)	7.04(.99)
Total EC	6.00(4.34)	1–18	1.26(.51)	1.77(.99)

Table 3
Correlations among learning gains, SRL, and EC variables – approach#1: full aggregation.

Variable	Learning gain	Planning	Monitoring	Strategy use	Total SRL	Nature of knowledge	Justification	Source evaluation	Epistemic aims
Planning	−.249								
Monitoring	−.087	.521*							
Strategy Use	−.046	.581**	.473*						
Total SRL	−.111	.787**	.804**	.889**					
Nature of Knowledge	−.097	.076	.051	.200	.151				
Justification	−.097	.519*	.104	.641*	.511*	.108			
Source Evaluation	−.197	.317	.330	.290	.369	.260	.441		
Epistemic Aims	−.288	.398	.179	.217	.277	−.140	.563**	.264	
Total EC	−.204	.467*	.287	.497*	.497*	.298	.765**	.910**	.473*

frequent than EC process behaviors. Strategy use ($M = 36.20$, $SD = 14.65$) behaviors were enacted more frequently than any other macro-level process. No macro-level SRL variables deviated greatly from normality. Source evaluation ($M = 4.20$, $SD = 2.98$) was the most frequent EC macro-level process, though it was less frequent than planning ($M = 6.50$, $SD = 4.73$), the least frequent SRL macro process. Table 3 provides correlational relationships among macro-level variables and learning gain scores. It is notable that a positive relationship between pretest knowledge (i.e., prior knowledge) and the frequency of macro-level SRL planning was found in this study, cohering with previous research (Greene, Costa, & Dellinger, 2011).

Regression analyses (see Table 4) revealed no statistically significant relationships between the SRL or EC macro-level variables and learning gain. The TotalSRL ($R^2 = .012$, *adjusted* $R^2 = -.043$) and Total EC ($R^2 = .042$, *adjusted* $R^2 = -.012$) variables were also not statistically significant predictors of posttest scores. These results suggest that Greene and Azevedo's (2009) method of aggregating micro-level variables into macro-level variables was not sufficiently nuanced for this sample or context. Therefore, we tested the second approach suggested by Greene et al. (2013).

3.2.2. *Approach #2: data-driven aggregation*

The second approach to analysis focused upon the micro-processes that the data suggested were most influential for learning. Less influential variables were filtered by the strength of their correlations to learning gain, which can be found in Appendices A and B. These micro-variables were then aggregated under four macro-variables: positively correlated SRL micro-variables (SRL+), positively correlated EC micro-variables (EC+), negatively correlated SRL micro-variables (SRL−), and negatively correlated EC micro-variables (EC−).

Table 5 illustrates the correlation cutlines that informed the creation of macro-variables at each cut point (i.e., where requisite correlations with learning gain were ±.1, .15, and .2). With each increase in the magnitude of the cutline for correlation with learning gain, fewer micro-variables were aggregated into the macro-variables for analysis. While we coded 82 micro-level SRL and EC behaviors, the correlation cutlines reduced this number to 29, 19, and 14, respectively, for the purpose of analysis. Table 6 gives descriptive statistics of the macro-level process variables for each of the three sets of macro-variables, by cutline. Table 7 indicates correlations among the macro-variables and learning gain at the three different cut points.

Table 8 indicates the results of pertinent regression models, each with the same macro-level categories, but constituted differently based on correlation cutline. With each iterative wave of selection, effect sizes for the regression model increased. At the .2 correlation cut line, the model demonstrated statistical significance ($R^2 = .606$; *adjusted* $R^2 = .500$; both $p < .01$). The last model indicated in Table 8 describes one unanticipated configuration of micro-process variables that yielded very meaningful and interesting results by an adjustment of the

Table 4
Regression results – approach#1: full aggregation.

Macro-level variables included in model:	Regressor 1	Regressor 2	Regressor 3	Regressor 4	Model Descriptors:
Monitoring Planning Strategy Use	Monitoring $\beta = .025$	Planning $\beta = -.345$	Strategy Use $\beta = .142$		$R^2 = .077$ $AR^2 = -.096$
Beliefs about Knowledge Justification Source Evaluation Epistemic Aims	Beliefs about Knowledge $\beta = -.132$	Justification $\beta = .195$	Source Evaluation $\beta = -.149$	Epistemic Aims $\beta = -.377$	$R^2 = .132$ $AR^2 = -.100$

β = beta weight, standardized coefficient.
*$p < .05$.
**$p < .01$.

Table 5
Correlations of micro-processes with learning gain ordered by degree of magnitude and correlation cutline for macro-level variable inclusion – approach#2: data-driven aggregation.

Negatively correlated variables			Magnitude (absolute value)	Positively correlated variables		
Construct	Variable	Correlation		Correlation	Variable	Construct
SRL	RGWM	−.583				
SRL	MPG	−.349				
EC	EMJ	−.343				
SRL	MUS	−.343				
EC	TJ	−.289				
EC	CKU	−.288				
EC	EAK	−.288				
SRL	PLAN	−.253				
SRL	ECAQ	−.246		.275	RN	SRL
EC	SEminus	−.236		.266	KE	SRL
EC	SE	−.214	±.2	.237	UPK	EC
SRL	COIS	−.189		.187	CEminus	SRL
SRL	EACminus	−.179				
SRL	CE	−.173	±.15			
SRL	SUM	−.155				
EC	TJL	−.150				
SRL	EACplus	−.149				
SRL	SKA	−.149		.133	JCplus	EC
SRL	RR	−.130		.130	SG	SRL
SRL	INTplus	−.118		.121	CEplus	SRL
SRL	FOKplus	−.104	±.1	.106	SQ	SRL

correlation cutline to a lower threshold that actually improved the model. In this fourth and "final" model ($R^2 = .661$; *adjusted* $R^2 = .571$; both $p < .01$), the macro-variables SRL+, SRL−, and EC− were defined by a correlation cutline of .2 while the EC + macro-variable was defined at .1. Importantly, compared to the third model, there was an overall improvement in beta weights for the equation in addition to a slight improvement in the effect sizes. The EC + beta weight improved noticeably from .067 in the .2 cutline model to .283 in the "final" model with the other variables being relatively the same in practical terms.

While findings regarding specific micro-level SRL and EC codes must be contextualized within the exploratory, situated nature of this study (e.g., Internet learning about vitamins), there were several interesting findings worth investigation. For example, model four in Table 8 indicates that reading notes and knowledge elaboration were positive predictors of learning gains. On the other hand, excessive planning and particular types of monitoring (i.e., MPG, MUS, ECAQ; see Appendix A), for this task and with this sample, were negative predictors of learning gains, on average. While not reaching statistical significance, verbalizing a belief in knowledge as situated, and invoking justifications for claims based upon their coherence with other knowledge claims, were positive predictors of learning gains (see Table 8).

3.2.3. Summary of results from the two different approaches for analyzing TAP micro-processes

The full aggregation approach utilized all relevant cognitive categories of SRL and EC and followed a more theoretical and conventional means of analysis. It did not yield any statistically significant outcomes during regression analyses. The second approach explored data-driven aggregation as an alternate mean of preparing, analyzing, and representing our data. Following a procedure of increasing selectivity, at the most selective correlation cut line, 14 micro-variables informed the analysis and the regression model achieved statistical and practical significance. A subsequent analysis modifying the cutline selection process included one additional micro-process improving the overall model. Our results indicated that SRL and EC processing, as modeled using our second approach, did predict learning gains and resulted in an optimal model that would not have been achieved otherwise, thus providing evidence in support of the fourth model in Table 8 as the most adequate answer to research questions 2 and 3.

4. Discussion

This study represents a first attempt to simultaneously measure critical components of digital literacy, i.e., SRL and EC, using powerful, but infrequently used TAPs, and relate those findings to learning gains in a digital environment. It is also the first attempt to measure a more

Table 6
Descriptive statistics for macro-level SRL and EC variables and totals – approach#2: data-driven aggregation.

Variable (correlation cutline)	Mean (*SD*)	Range	Skewness (*SE*)	Kurtosis (*SE*)
SRL+ (.2)	5.95(4.893)	0–20	1.501(.512)	2.725(.992)
EC+ (.2)	.05(.224)	0–1	4.472(.512)	20.000(.992)
SRL− (.2)	3.65(3.588)	0–12	.971(.512)	.056(.992)
EC− (.2)	2.05(2.235)	0–8	1.595(.512)	2.144(.992)
SRL+ (.15)	7.75(5.300)	0–22	1.143(.512)	1.669(.992)
EC+ (.15)	.05(.224)	0–1	4.472(.512)	20.000(.992)
SRL− (.15)	15.35(10.820)	2–49	1.562(.512)	3.867(.992)
EC− (.15)	2.05(2.235)	0–8	1.595(.512)	2.144(.992)
SRL+ (.1)	14.15(9.778)	0–47	2.067(.512)	6.433(.992)
EC+ (.1)	.15(.366)	0–1	2.123(.512)	2.776(.992)
SRL− (.1)	24.35(13.339)	2–54	.285(.512)	−.259(.992)
EC− (.1)	2.10(2.360)	0–8	1.683(.512)	2.379(.992)

Table 7
Correlations among learning gain, SRL, and EC variables defined by three different correlation cut points – approach#2: data-driven aggregation.

	Learning gain	SRL+ (.2)	EC+ (.2)	SRL− (.2)
SRL+ (.2)	.302			
EC+ (.2)	.237	.243		
SRL− (.2)	−.585*	.218	.023	
EC− (.2)	−.430	.010	−.216	.252
	Learning gain	**SRL+ (.15)**	**EC+ (.15)**	**SRL− (.15)**
SRL+ (.15)	.337			
EC+ (.15)	.237	.278		
SRL− (.15)	−.371	.184	−.008	
EC− (.15)	−.430	−.017	−.216	.212
	Learning gain	**SRL+ (.1)**	**EC+ (.1)**	**SRL− (.1)**
SRL+ (.1)	.272			
EC+ (.1)	.256	.096		
SRL− (.1)	−.393	.324	.107	
EC− (.1)	−.422	.075	−.323	.410

*$p < .01$.

expanded and delineated set of EC categories pertaining to justifications and epistemic aims (Chinn et al., 2011). Our analyses indicate that a sophisticated view of knowledge as situated and particular, as well as frequent use of elaborative learning strategies, were positive predictors of learning in this environment, with this sample. In line with previous research on Internet learning (e.g. Tu et al., 2008), we assert the results of this study indicate that SRL skills are a critical component of digital literacy. In addition, we found that searching, vetting and integrating information into the meaning-making process during online learning requires both effective SRL and EC skills. While limited by the exploratory and situated nature of the study, our substantive findings support Greene et al. (2013) claims that SRL and EC processing may be highly contextual, and that particular tasks and learning environments may necessitate the use of specific learning behaviors. Finally, given the utility of meaningful, data-driven groupings of SRL and EC micro-processes, our work suggests that TAPs may afford researchers even more insight into the nature of these psychological phenomena than has been realized using previous approaches to analysis (e.g. Greene & Azevedo, 2009).

4.1. Limitations

The sample size of 20 participants is relatively small in terms of statistical analysis, and aforementioned issues of power prevent any generalizable claims based upon the results of this study. Likewise, research questions 2 and 3 were exploratory both in technique and in substance; therefore, further research is needed to replicate both the utility of the data-driven aggregation technique (Greene et al., 2013) as well as the substantive findings. Another limitation concerns the nature of the task assigned for capturing EC activity. Tasks that do not require participants to make an argument or justify their claims seem less likely to elicit the kinds of EC processing that can be captured using TAPs, compared to tasks that make explicit the need for participants to provide rationales for their claims.

Table 8
Comparison of regression models – approach#2: data-driven aggregation.

Correlation cutline	Regressor descriptors: SRL+	Regressor descriptors: EC+	Regressor descriptors: SRL−	Regressor descriptors: EC−	Model descriptors
.1	$\beta = .332$	$\beta = .233$	$\beta = -.414$	$\beta = -.160$	$R^2 = .39$ $AR^2 = .227$
Micro-processes meeting cut line:	RN + KE + CEminus + SG + CEplus + SQ	UPK + JCplus	RGWM + MPG + MUS + PLAN + ECAQ + COIS + EACminus + CE + SUM + EACplus + SKA + INTplus + RR + FOKplus	EMJ + TJ + CKU + EAK + SEminus + SE + TJL	
.15	$\beta = .378$	$\beta = .073$	$\beta = -.344$	$\beta = -.313$	$R^2 = .419$ $AR^2 = .265$
Micro-processes meeting cut line:	RN + KE + CEminus	UPK	RGWM + MPG + MUS + PLAN + ECAQ + COIS + EACminus + CE + SUM	EMJ + TJ + CKU + EAK + SEminus + SE	
.2	$\beta = .405^{*}$	$\beta = .067$	$\beta = -.611^{**}$	$\beta = -.225$	$R^2 = .606^{**}$ $AR^2 = .500^{**}$
Micro-processes meeting cut line:	RN + KE	UPK	RGWM + MPG + MUS + PLAN + ECAQ	EMJ + TJ + CKU + EAK + SEminus + SE	
SRL+ @ .2 EC+ @ .1 SRL− @ .2 EC− @ .2	$\beta = .388^{*}$ (cutline @ .2)	$\beta = .283$ (cutline @ .1)	$\beta = -.697^{**}$ (cutline @ .2)	$\beta = -.150$ (cutline @ .2)	$R^2 = .661^{**}AR^2 = .571^{**}$
Micro-processes meeting cut line:	RN + KE	UPK + JCplus	RGWM + MPG + MUS + PLAN + ECAQ	EMJ + TJ + CKU + EAK + SEminus + SE	

β = beta weight, standardized coefficient.
AR^2 = adjusted r-squared.
*$p < .05$.
**$p < .01$.

4.2. Future directions

This study provides evidence that SRL and EC are relevant aspects of digital literacy, and predict learning of complex science topics on the Internet. Further investigation into the particularities of SRL and EC in online environments will help elucidate this proposition. This study suggests that the full capacity of TAP methodology is yet unrealized by researchers. More research into alternative and meaningful ways of analyzing TAP data should help to maximize its utility and address measurement crises within the fields of SRL (Veenman, 2007; Winne & Perry, 2000) and EC (Greene & Yu, 2014; Hofer & Sinatra, 2010), particularly regarding its use as an alternative to the notoriously problematic self-report measures used in many previous studies (cf. DeBacker et al., 2008). Future research using TAPs to measure SRL and EC should include more defined learning goals involving the need to argue for, and justify, conclusions drawn from multimodal presentations on the Internet.

4.3. Conclusion

In this study, we found that SRL and EC processing were related to learning gains in a study of digital learning, and that data-driven aggregation techniques were a viable method of preparing, analyzing, and representing TAP data regarding these phenomena. We consider the predictive relationships between SRL and EC to learning online as warrant for our inclusion of those phenomena in the definition of digital literacy, and for further investigation of these complex cognitive phenomena. Finally, we demonstrated how TAP data collection and analysis can be successfully applied by researchers to the study of complex, learning behaviors when engaging science topics in the multimedia, hyperlinked contexts of the Internet.

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Appendix A

Self-regulated learning (SRL) coding scheme and correlations with learning gain

SRL macro-level category: planning

Micro-level category	Code	Description	Correlation with learning gain
Planning	PLAN	Learner stated two or more learning or time goals	−.253
Recycle Goal in Working Memory	RGWM	Restating the goal (e.g., question or parts of a question) in working memory	−.583
Sub-Goal	SG	Learner articulates a specific sub-goal that is relevant to the experiment-provided overall goal. Must verbalize the goal immediately before clicking on the relevant sub-section AND must immediately carry out some action relevant to the goal [i.e., can't drop the goal immediately]	.130
Time Planning	TP	Participant refers to the number of minutes remaining AND indicates whether a goal can be met during that time	−.071

SRL macro-level category: monitoring

Micro-level category	Code	Description	Correlation with learning gain
Content Evaluation (Plus)	CE+	Stating that any just-seen text, diagram, or video is relevant to learning or is good	.121
Content Evaluation (Minus)	CE−	Stating that any just-seen text, diagram, video is irrelevant or not helpful to learning	.187
Content Evaluation (Neutral)	CE	Evaluating any just-seen text, diagram, or video without definitive conclusion regarding relevance to learning.	−.173
Expectation of Adequacy of Content (Plus)	EAC+	Expecting that a certain content (e.g., section of text, diagram, video) will be adequate given the current goal	−.149
Expectation of Adequacy of Content (Minus)	EAC−	Expecting that a certain content (e.g., section of text, diagram, video) will not be adequate given the current goal	−.179
Expectation of Adequacy of Content (Neutral)	EAC	Evaluating adequacy of presented content given the current goal without definitive conclusion	.063
Emotion Monitoring	EM	Participant realizes that he/she is having an emotional response due to some aspect of the learning task.	.070
Feeling of Knowing (Plus)	FOK+	Learner is aware of having read or learned something in the past and having some understanding of it	−.104
Feeling of Knowing (Minus)	FOK−	Learner is aware of not having read or learned something in the past	−.093
Feeling of Knowing (Neutral)	FOK	Learner is aware of having read or learned something in the past but does not feel certain of the content or understanding it.	.043
Judgment of Learning (Plus)	JOL+	I get it! OR This makes sense	.009
Judgment of Learning (Minus)	JOL−	I don't get it! OR This doesn't makes sense	−.039
Judgment of Learning (Neutral)	JOL	I kind of get it, but I kind of don't. OR This does and doesn't makes sense to me.	N/A[a]
Monitor Progress Toward Goals	MPG	Assessing whether previously-set goal has been met	−.349
Monitor Use of Strategies	MUS	Participant comments on how useful a strategy is/was	−.343
Self-Questioning	SQ	The participant asks a question relevant to the task, but does not articulate a specific plan to investigate the answer. Indicates that the participant has recognized a gap in understanding.	.106
Time Monitoring	TM	Participant refers to the number of minutes remaining	.036

SRL macro-level category: strategy use

Micro-level category	Code	Description	Correlation with learning gain
Coordinating Informational Sources	COIS	Using pointing or verbalizing the matching of elements of two different representations, e.g., drawing and notes. Either representation can be in the environment or in participant's notes.	−.189
Control Video	CV	Using pause, start, rewind, or other controls in the digital animation.	.160
Draw	DRAW	Making a drawing or diagram to assist in learning	N/A1
Evaluate Content as Answer to Question	ECAQ	Statement that what was just read and/or seen meets an experimenter posed question	−.246
Emotion Regulation	EM	Participant actively attempts to control emotional response to some aspect of the learning task.	.043
Inferences	INF	Drawing a conclusion based on two or more pieces of information that were read, seen, or heard in the hypermedia environment in same time period, roughly	−.015
Knowledge Elaboration	KE	Elaborating on what was just read, seen, or heard with prior knowledge	.266
Memorization	MEM	Learner tries to memorize text, diagram, etc.	−.053
Prior Knowledge Activation	PKA	Searching memory for relevant prior knowledge either before beginning performance of a task or during task performance	−.080
Read Notes	RN	Learner reads over his/her own notes, drawings, etc.	.275
Re-reading	RR	Re-reading or revisiting a section of the hypermedia environment	−.130
Search	SEARCH	Searching the hypermedia environment	.022
Select New Informational Source	SNIS	Using features of the hypermedia environment to access a new representation and/or a new section of the environment (clicking on hyperlinks, items in Table of Contents, back arrow)	.185
Self-Knowledge Activation	SKA	The participant verbalizes that he or she is going to invoke a strategy because it is helpful to him/her personally. Or participant verbalizes that he/she is NOT going to invoke a strategy because it is NOT helpful to him/her.	−.149
Summarization	SUM	Verbally restating what was just read, inspected, or heard in the hypermedia environment	−.155
Taking Notes	TN	Learner writes down information	.053

SRL macro-level category: interest

Micro-level category	Code	Description	Correlation with learning gain
Interest (Plus)[2]	INT+	Learner has a certain high level of interest in the task or in the content domain of the task.	−.118
Interest (Minus)	INT−	Learner has a low level of interest in the task or in the content domain of the task, used for any representation.	.090
Interest (Neutral)	INT	Learner makes some interest-related expression regarding the task or in the content domain of the task indicating neither high nor low interest.	N/A1

[a] N/A indicates that the micro-process was not activated by any of the 20 participants during their 30-min learning sessions resulting in no data for this category.

Appendix B

Epistemic cognition (EC) coding scheme and correlations with learning gain

EC macro-level category: beliefs about knowledge

Micro-level category	Code	Description	Correlation with learning gain
Simple Knowledge (Simple)	SKS	Participant states that knowledge is a set of relatively independent facts.	N/A1
Simple Knowledge (Complex)	SKC	Participant states that knowledge is primarily a set of highly interconnected, complex knowledge claims.	N/A1
Universality of Knowledge (Universal)	UKU	Knowledge claims are seen as applying in every situation, and every context.	N/A
University of Knowledge (Particular)	UPK	Participant states that knowledge is seen as highly contextualized or situated.	.237
Certain Knowledge (Certain)	CKC	Participant states that what is considered knowledge today will also be considered knowledge at any point in the future	N/A1
Certain Knowledge (Uncertain)	CKU	Participant states that what is considered knowledge today may not be considered knowledge in the future; knowledge can change or is defeasible	−.288

EC macro-level category: justification

Micro-level category	Code	Description	Correlation with learning gain
Justification by personal perception (Plus)[3]	JPP+	Participant uses one of his/her five senses as warrant for claim as knowledge.	N/A1
Justification by personal perception (Minus)	JPP−	Participant uses one of his/her five senses as reason to disregard claim as knowledge.	N/A1
Justification by personal perception (Neutral)	JPP	Participant uses one of his/her five senses to evaluate claim as knowledge but without definitive conclusion.	N/A1
Justification by Memory (Plus)	JM+	Participant establishes warrant for knowledge claim based upon recalling it from his/her memory.	N/A1
Justification by Memory (Minus)	JM−	Participant denies a knowledge claim based upon the inability to recall it from his/her memory.	N/A1

(*continued*)

Micro-level category	Code	Description	Correlation with learning gain
Justification by Memory (Neutral)	JM	Participant uses his/her memory to evaluate claim as knowledge but without definitive conclusion.	N/A1
Justification by Testimony (Plus)	JT+	Participant establishes a warrant for a claim based upon the views/arguments/beliefs of someone that he/she believes is an authority on the matter.	N/A1
Justification by Testimony (Minus)	JT−	Participant denies a claim based upon the views/arguments/beliefs of someone that he/she believes is an authority on the matter.	.060
Justification by Testimony (Neutral)	JT	Participant evaluates claim as knowledge based upon the views/arguments/beliefs of someone that he/she believes is an authority on the matter but without definitive conclusion.	.047
Justification by Coherence (Plus)	JC+	Participant establishes a warrant for a claim based upon the claim aligning with, agreeing with, supporting, or being supported by, other knowledge claims that he or she believes are sufficiently warranted.	.133
Justification by Coherence (Minus)	JC−	Participant denies a claim based upon the claim aligning with, agreeing with, supporting, or being supported by, other knowledge claims that he or she believes are sufficiently warranted.	N/A1
Justification by Coherence (Neutral)	JC	Participant evaluates claim as knowledge based upon it aligning with, agreeing with, supporting, or being supported by, other knowledge claims that he or she believes are sufficiently warranted; but without definitive conclusion.	.060
Justification by Rationality/ Logic (Plus)	JRA+	Participant establishes warrant for claim based upon thinking, logic, reasoning.	N/A1
Justification by Rationality/ Logic (Minus)	JRA−	Participant denies claim based upon thinking, logic, reasoning.	N/A1
Justification by Rationality/ Logic (Neutral)	JRA	Participant evaluates claim as knowledge based upon thinking, logic, or reasoning but without definitive conclusion.	N/A1
Justification by Replication (Plus)	JRE+	Participant establishes warrant for claim based upon repeated tests of the claim. This code may be more common in the sciences than other domains.	N/A1
Justification by Replication (Minus)	JRE−	Participant denies claim based upon repeated tests of the claim. This code may be more common in the sciences than other domains.	N/A1
Justification by Replication (Neutral)	JRE	Participant evaluates claim as knowledge based repeated tests of the claim but without definitive conclusion.	N/A1
Establishing Multiple Justifications (Plus)	EMJ+	Participant established a warrant for a claim based upon the support of multiple sources of justification (e.g., testimony, coherence, rationality).	N/A1
Establishing Multiple Justifications (Minus)	EMJ−	Participant denies a claim based upon the support of multiple sources of justification (e.g., testimony, coherence, rationality).	−.053
Establishing Multiple Justifications (Neutral)	EMJ	Participant evaluates claim as knowledge based upon the support of multiple sources of justification (e.g., testimony, coherence, rationality) but without definitive conclusion.	−.343
Justification by Religion (Plus)	JR+	Participant establishes the warrant for a claim based upon the claim of a religious source.	N/A1
Justification by Religion (Minus)	JR−	Participant establishes the warrant for a claim based upon the claim of a religious source.	N/A1
Justification by Religion (Neutral)	JR	Participant evaluates claim as knowledge based upon the claim of a religious source but without definitive conclusion.	N/A1
Tentative Justification (High)	TJ+	Stating confidence or likelihood about the veracity of a knowledge claim without definitively accepting it.	N/A1
Tentative Justification (Low)	TJ−	Stating doubt or unlikelihood about the veracity of a knowledge claim without definitively denying it.	−.150
Tentative Justification (Neutral)	TJ	Stating that a particular knowledge claim is "possibly" or "tentatively" justified true belief without indication of a strong tendency either for or against its veracity.	−.289

EC macro-level category: source evaluation

Micro-level category	Code	Description	Correlation with learning gain
Source Evaluation (Plus)	SE+	Statements indicating that the participant is investigating the quality of the source of a knowledge claim. Statements indicate that the source in question can be considered trustworthy for providing knowledge claims whose veracity is high.	.032
(Minus)	SE−	Statements indicating that the participant is investigating the quality of the source of a knowledge claim. Statements indicate that the source in question cannot be considered trustworthy for providing knowledge claims whose veracity is high.	−.236
(Neutral)	SE	Statements indicating that the participant is investigating the quality of the source of a knowledge claim. Despite clearly evaluating the source, no definitive claim is made regarding its trustworthiness for providing knowledge claims whose veracity is high.	−.214
Inferring Author Bias	IAB	Participant indicates a source of knowledge may be bias in some way.	−.063

EC macro-level category: epistemic aims

Micro-level category	Code	Description	Correlation with learning gain
Epistemic Aim: Understanding	EAU	Participant's goal is to have deep knowledge of not only facts but also warrants for how processes work (if relevant), etc.	N/A1
Epistemic Aim: Knowledge	EAK	Participant states that he or she wants to "know" facts with either the explicit or implicit indication that sufficient warrant/justification is also required; seems to only desire declarative or low-level procedural knowledge of the phenomenon	−.288
Epistemic Aim: Information	EAI	Participant simply wants to acquire information without judging whether it is sufficiently warranted.	N/A1

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