Leveraging Learners' Metacognitive Activities for Recommendation in Technology Enhanced Learning Systems

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There has been a growing interest in assisting learners develop control over their learning and behaviour. Metacognition — the ability to think about thinking — can be an effective learning strategy that encourages learners take control of their learning. Typically, while reading, learners engage in a number of metacognitive reading activities e.g. text marking, highlighting. This study examines the effectiveness of utilizing the metacognitive activities generated by learners as a preference elicitation method to guide the recommendation of personalized learning resources. Providing appropriate resources that facilitate personalized learning is considered imperative given that learning differs from one learner to another.

Keywords: metacognitive learning activities, personal recommender system, technology enhanced learning

INTRODUCTION

Today, educational institutions are faced with the continuous need to discover methods that improve learning, learner engagement, and the effective use of learning resources. The art of learning has been considered as a process of thinking that allows us to use reasoning in an effective manner (Ossa-Cornejo, 2018). To learn effectively and meaningfully, Ossa-Cornejo (2018) argues that the use of cognitive strategies alone is not enough, rather the inclusion of reflective strategies (metacognition) that evaluate the process and strategies of learning should also be used. Learning is also no longer considered a part of childhood and youth alone, but is a lifelong activity. It is not limited to the context of an educational institution, but also includes informal learning, professional learning at work, personal development, and learning in Massive Open Online Courses (MOOCs), (Drachsler, 2009). Therefore, the development of good individual learning (self-directed learning) strategies, as well as systems that facilitate self-directed learning are important.

Self-directed learning can be described as a process in which individuals take the initiative, with or without the help of others, in diagnosing their learning needs, formulating learning goals, identifying human and material resources for learning, choosing appropriate learning strategies and evaluating learning outcomes (Knowles, 1975). Self-directed learning can be regarded as a skill, where the individual must know how to set goals, what is needed to achieve those goals, and how to actually attain these goals, and a useful skill for lifelong learning. Developments in educational technology have supported the creation of complex Technology Enhanced Learning Environments (TELEs), which provide learners with rich opportunities to use digital technologies to interact with, to configure and to control their learning environments, to communicate with other learners, and to receive quick feedback from all the actors involved (Persico and Steffens, 2017). TELEs are able to offer learners freedom and choice thus providing them with the opportunity to make strategic decisions about their own learning – this allows learners to practice self-directed learning (Persico and Steffens, 2017).

Persico and Steffens (2017) identified three important areas in which TELEs could be beneficial to self-directed learning: metacognition, personalization and assessment. The term metacognition was coined by Flavell (1971) and can be defined as "cognition about cognition", that is, the knowledge concerning one's own cognitive processes. Metacognition, in TELEs is facilitated by the capability for online learning systems to keep track of the learning dynamics of each learner, and this allows learners to go back to their previous actions and reflect on their learning processes, strategies and progress. The concept of personalization is concerned with the possibility for the learner to control and configure their own environment in order to make the learning process optimal, while the concept of assessment presents a means to provide feedback to the learner based on his/her performance to improve and accelerate learning (Sadler, 1998). With the rapidly increasing amount of learning materials and resources available online, it is becoming more difficult for learners to find appropriate information or learning material to satisfy their needs. Many studies report information overload as one of the main problems that learners encounter in online learning and when searching for the "right" information to satisfy their needs (Manouselis et al., 2011). Searching for relevant information is therefore considered a pivotal activity in teaching and learning (Drachsler, 2009).

Learning is an active cognitive activity that differs from one learner to another (Shishehchi et al., 2011); each learner has individual, goals, learning style, among others characteristics. Some learners may be highly self-motivated and learn by exploration, while other students prefer some specific guidance in a structured way. This brings about the need for the development of technology that would cater to the individual learning requirement of the learner. Personalized learning describes the search for, and the recommendation of, potential learning activities that are the most suitable to the individual learner (or learner group) (Drachsler, 2009). Personalized learning is said to occur when the learning activities has been designed to fit the needs, goals, talents, and interests of the learners (Klasnja-Milicevic, 2011). To facilitate self-directed learning, a recommender system (technology) would be required to assist learners with determining available learning activities, materials and resources that would match their personal needs, preferences, prior knowledge and current situation to attain their learning goals. In this context, a recommendation system is considered a resourceful software tool that could be used to identify interesting learning materials from a large pool of resources. Recommendation systems are also able to reduce the burden of information overload by recommending the "right" information at the right time and in the right format (media) of the learner's interest.

With respect to recommendation in the TELEs, the concept of metacognition can be captured by the strategic selection of recommended learning materials and the strategic processing of the selected materials (Zhou and Xu, 2012). There exists a number of metacognitive activities a learner could engage in while learning. We are focusing on the metacognitive activities related to reading comprehension, because it constitutes the most common context where learning occurs (Zhou and Xu, 2012). Based on the metacognitive activities associated with reading, recommendations would be made to facilitate comprehension, recall and deeper text processing. The metacognitive reading strategies: organization, note taking, underlining/ highlighting are learning strategies that are focused on reading and are essential to the learning process. This is because they could help a learner find connections within a body of new information; pay attention to, encode new material and provides external storage of information for later studies; determine portions of a body of text that are important to learn and what is trivial respectively (Ormrod, 2012). These metacognitive and learning strategies also support the notion of personalization, because the strategies allow the learners to take control over the learning process. Therefore, it is assumed that TELEs that includes the possibility to take notes, bookmark, highlight portions of the content favors the practice of self-directed learning (Persico and Steffens 2017).

In general, recommender systems provide suggestions of objects to a user, and are widely used in the e-commerce and e-learning domains. In the e-commerce domain, recommendation is a popular personalization technology where the objects for recommendation are products (such as movies, books) and the users are the customers. In the e-learning domain however, the objects for recommendation are learning materials, and the users are the learners or students. The main objective of the recommender systems, regardless of the domain in which it is applied, is to predict objects that are of interest or relevant to a user. Recommender systems rely heavily on information related to a given domain. The dependency restricts the possibility of applying the recommendation strategy used in one domain to another. For example, personalized recommendation in the e-commerce setting is based on what other users like/ratings, while in the e-learning/TEL setting, it is argued that to achieve personalized recommendations, the recommendation tool should also take into account other features peculiar to each learner, such as: current learning goal, prior knowledge, and other learner characteristics (Drachsler, 2009).

This study examines the possibility of the design of a recommender system using the metacognitive activities a learner engages in while reading to achieve personalized learning; where the metacognitive study activities include creating bookmarks, highlighting portions of a text, taking notes, tags, among others. There are several reasons why learners engage in metacognitive activities while reading (e.g highlighting/text marking). From a text processing perspective, the act of deciding what to highlight and otherwise could enable the learner to process the textual information at a deeper and more evaluative level than they would when simply reading it (Craik and Lockhart 1972; Nist and Hogrebe 1987). Another reason is that highlighting could make the marked portion of text more memorable since it stands out from the rest of the unmarked text, which could facilitate recall. Finally, the highlighted text could serve as a guide for later studies (Kornell and Bjork 2007). Based on these reasons we consider the highlights learners make as a reflective practice that provides insight to the learner's comprehension, and could also reveal the information seeking needs of the learner. By considering the highlights as an information seeking need, the highlights learners make serve as input to the recommender system, which it uses to make recommendations. Typically, the information seeking needs of a learner are expressed using a search query in a search engine. However, search queries do not always return relevant information, due to reasons such as poor queries and natural language ambiguities (Batista, 2007). Therefore, a more cognitive approach to identifying the learners' information needs could be achieved by examining the interactions the learner engages in with the learning materials.

The recommendation approach developed in this study covers two (metacognition and personalization) of the three important areas in which technology enhanced learning environments can be beneficial to self-directed learning identified by Persico and Steffens (2017). The third important area of assessment has been previously published. In which automatic question generation from text was adapted to an online and self-directed learning platform (Odilinye et al., 2015). The automatic questions generated were aligned to the specified pedagogical goals and to a learner's model and provided formative assessment to the learner. To identify the "right" learning material for a learner based on the metacognitive activities, we propose to use probabilistic topic modelling approach to analyze and identify the topics/themes of interest to the learner from his/her interactions. Using the information inferred from the learner's interaction, the system is then able to identify and retrieve appropriate learning resources that match the learner's information seeking needs.

METACOGNITION AND SELF-REGULATED LEARNING

The traditional role of the classroom teacher is significantly changing with time. According to Williamson (2015), this change is due to the developments in the definition of learning. Previously, learning was associated with knowledge absorption, however, it is now recognized as the active construction of knowledge (de Jager et al., 2005). Today, it is argued that learning should be about how to deal with (new) challenging situations or problems and not necessarily to regurgitate or apply objective facts only, (Boud, 2001). This understanding of learning has resulted in a number of pedagogical developments, one being the increased need for learners to be self-directed (Williamson, 2015), and thus learning how to learn has become an important educational issue. Self-directed learning enhances the learner's ability to 'manage self', and this competency encompasses other concepts such as self-motivation, self- belief, solving problems, working independently, setting goals and assessing one's own learning. It is advocated that the skill self-directed learning should be taught and encouraged at all levels of education as it has been shown that learners who can manage themselves demonstrate resourcefulness, reliability and resiliency (Ministry of Education, 2007).

Self-directed learning, self-planned learning, self-education, self-regulated learning, independent learning and open learning are concepts that (loosely speaking) define the same phenomenon (Dagal and Bayindir, 2016). Self-directed learning can be described as a process in which individuals take the initiative, with or without the help of others, in diagnosing their learning needs, formulating learning goals, identifying human and material resources for learning, choosing and implementing appropriate learning strategies, and evaluating learning outcomes (Knowles, 1975). According to Zimmerman (1989), a learner can be described as self-regulated to the degree that they are metacognitively, motivationally and behaviourally active participants of their learning process, where they initiate and direct their efforts to acquire knowledge and skills without relying on other agents (e.g. parents, teachers) for instructions. Although, the two concepts: self-regulated learning and self-directed learning can be argued to be different, they share similarities such as learners' independence, active engagement, goal-oriented behaviour and control of the learning process (Loyens et al., 2008). These similarities are the underlying learning conditions that this study addresses with providing an appropriate TELE which facilitates learning and assists the learner in the achievement of the learning goal by the recommendation of relevant learning resources. Self-regulated learning has three components: motivation, metacognition, and learning behaviour (Zimmerman, 1990). In the context of self-regulated learning, motivation refers to a learner's self-efficacy and autonomy, and is closely linked to a learner's goal (Bolhuis 2003; Zimmerman 1990). The achievement of the learning goal helps the learner pay attention to the learning process and deploy appropriate cognitive strategies (Bolhuis, 2003). The term metacognition in relation to self-regulated learning refers to a learner's ability to think consciously about their cognition and have control over their cognitive processes (Zimmerman, 1989). Metacognition can be defined as monitoring and controlling cognition, in other words, the individual's thinking of his/her own cognitive processes (Flavel 1989). Metacognition can be categorized in two groups: knowledge about cognition, and metacognitive skills. Knowledge about cognition relates to learners having knowledge about their own cognitive activities and cognitive strategies (Dagal and Bayindir, 2016) while metacognitive skills define the processes that organize and control cognition, such as: planning, monitoring and evaluating (Boekaerts, 1999).

Recently, the concept of metacognition has emerged as a popular area of study. A possible reason for this is that there exists a positive relationship between metacognitive elements and academic success (Bagceci and Sarica, 2011). Meta-cognition has been identified to be closely related to learning processes, learning goal attainment and academic success because it makes the learner aware of their thinking processes and the ability to control their cognitive system (Baltaci and Akpinar, 2011). Learners with high metacognitive awareness are therefore aware of what they know and do not know, and are successful at planning, information management, contracting strategies, monitoring, debugging and evaluating. Thus, it can be said that metacognition has a positive effect on learning success and goal achievement (Schraw and Sperling-Dennison, 1994; Zimmerman and Schunk, 2001).

Learning behavior, a third component of self-regulated learning, entails the decisions and actions the learners make in order to optimize their learning environment (Zimmerman, 1990). This includes making available appropriate tools and resources that empowers the learner, give the learner control over the learning process, as well as fosters self-direction, collaboration and cooperation that encourage the idea of learning community (Bolhuis and Voeten, 2001). Based on this notion, we hypothesize that a TELE equipped with adequate metacognitive tools and that allows for collaboration would truly facilitate self-regulated learning. In the next section, we discuss metacognitive standards and study strategies that learners deploy during learning.

Metacognitive Standards, Reading Strategies

Academic learning has been regarded as a self-regulated process where learners use and direct their thoughts, feelings and actions to achieve learning goals (Zimmerman, 2002). The process of self-regulated learning consists of sub-processes which includes goal setting, planning and selecting strategies, monitoring and evaluating performance (Winne and Hadwin, 1998). Monitoring and evaluating one's learning is a metacognitive process that is integral to self-regulated learning (Tobbias and Everson, 2000; Winne, 2001). Based on this perspective, the process of monitoring requires the use of a set of metacognitive standards which could be used to compare the current status or condition of learning (Winne, 2001). The metacognitive standards are created by the learner and are influenced by both external task and cognitive conditions (Winne and Hadwin, 1998). Task conditions include task instructions, resources available for the learner, and the learning environment. Cognitive conditions include factors such as learners' past learning experiences, personal dispositions, beliefs about knowledge and knowing, domain knowledge, and knowledge of study tactics and strategies (Marzouk, 2018).

Reading is a complex cognitive process involving various sub processes (Mckeown and Beck, 2009) some of which are metacognitive. Choosing when to use a reading strategy, how to use it, evaluating and monitoring comprehension, and controlling strategy and use are examples of metacognitive processes taking place while reading (Baker and Brown, 1984). There are a number of metacognitive reading activities that a learner may engage in; also a number of systems that support self-regulated learning have been developed to facilitate some of the metacognitive reading strategies and activities. In the next section, we review some of the existing systems designed to support metacognitive reading activities.

Related Work on Metacognitive Reading Strategies in Self-Regulated Learning Settings

There exists a number of learning environments or platforms that have been designed to support self regulated learning. MetaTutor, a hypermedia learning environment designed by Azevedo et al., (2008) to detect, model, trace, and foster students' self regulated learning about human body systems such as the circulatory, digestive, and nervous systems. MetaTutor entails four phases to train students on SRL processes and to learn about the various human body systems. The phases include (1) modelling of key SRL processes, (2) discrimination task where learners choose between good and poor use of these processes, (3) a detection task where learners get to see video clips of human agents engage in similar learning tasks and are asked to stop the video whenever they see the use of a SRL processes (and then they have to indicate the process from a list), and (4) the actual learning environment used to learn about the biological system. Overall, the system was designed to provide adaptive human scaffolding, that addresses both the content of the domain and the processes of self regulated learning, which enhances students' learning about challenging science topics with hypermedia.

A Narrative-centred learning environment for eighth grade Microbiology, Crystal Island (Rowe et al., 2009) was designed to provide significant potential for enhancing students' learning experiences. It deploys engaging interactive narrative experiences that are pedagogically effective and tailored to an individual student to provide problem-solving guidance that simultaneously enhances students' self-efficacy for self regulated learning. Due to their interactive nature, narrative-centred learning environments are designed to cope with a wide range of actions a student may perform, thus providing them with a strong sense of control – important for supporting motivation and self regulation. Some of the actions a student can perform with Crystal Island includes: pick up and manipulate objects, take notes, view posters, operate lab equipment, and talk with non-player characters. nStudy, a web application that offers learners a wide array of tools for identifying and operating on information they study.

Self explanation, a metacognitive reading strategy describes the process of explaining text to one's self either orally or in writing. These explanations are generally based on information contained in the discourse context and can be initiated while reading (McNamara and Magliano, 2008). A number of frameworks, systems have been developed to encourage and initiate self-explanation while reading for s number of domains (e.g maths). Self-Evaluation Coach (SE-Coach) developed by Conati and VanLehn (2000) is a scaffolding tool meant to encourage students to spontaneously self-explain. This is achieved at two levels:

the first level of scaffolding is provided by a masking mechanism that presents different parts of an example covered by grey boxes, each corresponding to a "unit" of information. When the student moves the mouse over a box, it disappears, revealing the text or graphics under it. The second level of scaffolding is provided through specific prompts to self-explain. Whenever the student unmasks a piece of the example, if it contains an idea worthy of explanation the interface will append a button labeled "self-explain". Pressing the button produces simple prompts to initiate self-explanations in terms of domain principles. Tajika et al., (2007) examined the effect of self-explanation on word problem solving. The results of user study performed Tajika et al., (2007) showed that students in the self-explanation group outperformed students in the other groups on both the ratio word problem test and on the transfer test. In addition, high explainers who generated more self-explanations relating to deep understanding of worked out examples outperformed low explainers on both ratio word problem and transfer tests. NORMIT, a constraint-based tutor developed by Mitrovic (2002) teaches data normalization and supports self-explanation. In comparison to other self-explanation systems, NORMIT requires an explanation from users for each action that is performed for the first time and not at every step. For subsequent actions of the the same type, an explanation is required only if it is performed incorrectly. The results of the user study performed by Mitrovic (2002) revealed that self-explanation increased problem solving skills and better conceptual knowledge.

These brief review of existing work highlights the benefits of developing systems that facilitate metacognitive reading activities as well as the effects metacognition had on learning experience.

Our Approach: Metacognitive Reading Strategy

Having examined the effectiveness and benefits of adopting metacognitive reading strategies to learning, in this study, we investigated the capability of a different set of metacognitive reading activities to enhance learning as well as guide further studies — recommendation of supplementary learning resources. Text marking, a reading strategy, has been identified as the most preferred strategy among college students (Gier et al, 2009). Many college students reported that marking textbooks increased concentration, enhanced comprehension, and facilitated review (Nist and Kirby, 1986), and is perceived as effortless, requires no training and minimizes material to study and review (Blanchard and Mikkleson, 1987). Text marking is also widely promoted, study skills courses at schools and universities advocate text marking as an effective study strategy (Wade and Trathen, 1989). Other common reading strategies that learners engage in are knowledge/concept maps and note taking (Marzouk, 2018). While research has been done to investigate the efficacy of each of these study strategies (comparing and contrasting study techniques) on reading comprehension, information retention, recall, knowledge transfer, among others, in this study, we investigate the use of a study strategy (text marking) for recommendation of learning materials.

Although text marking involves both cognitive and metacognitive processes, adopting Winne's (2001) "if-then" view of a reading strategy provides deeper understanding of what takes place when a reader is interacting with information. According to this view, if a learner judges a set of criteria is satisfied then a study strategy is applied (Marzouk, 2018). The judgment component of this sequence is a metacognitive act because it involves learner's thinking about and using self-created standards to guide learners' cognition about the text (Winne, 2001). Applying this definition to text marking, when learners are reading and marking text they use metacognitive criteria to identify which information merits marking (Marzouk, 2018). Given a reading objective (e.g., "Read the following text and mark important information"). Learners use the reading objectives to create standards to guide judgment when reading text about which text to mark and during study, learners use metacognitive standards created in relation to objectives to judge whether to mark. If learners are not required to mark overtly, learners still use these standards to metacognitively judge whether a text segment is worthy of attention (Marzouk, 2018).

Information worthy of attention does not necessarily mean it is important. Therefore, a distinction between two key concepts: importance and relevance, is imperative. According to McCrudden and Schraw (2007) "relevance is the degree to which a text segment is germane to a specific task or goal, whereas importance is the degree to which a segment contains essential information needed to understand a text" (p.114). Important segments in text often are cued by the author (e.g., by typographical cues, order of presentation). Thus importance is text-related. Relevance, on the other hand, is determined by learner's objectives or standards. It is a text-external phenomenon (McCrudden and Schraw, 2007). A relevant text segment does not need to be important. Based on McCrudden and Schraw's (2007) concept of relevance, learners generate metacognitive standards in relation to cognitive and task conditions, then use those standards to judge whether a text segment deserves marking (Marzouk, 2018). Marked text indicates that a learner judged it relevant. Thus, the process of determining whether a text segment should be marked or otherwise has both cognitive and metacognitive components. The cognitive component includes text encoding processes and accessing prior knowledge to comprehend what is read; the metacognitive part involves (a) monitoring, applying and continuously adjusting standards, and (b) controlling processes leading to mark text or not (Marzouk, 2018).

Self-Regulated Learning and Motivation

In the context of self-regulated learning, motivation refers to a learner's self-efficacy and autonomy, and is closely linked to a learner's goal (Bolhuis 2003; Zimmerman 1989). The achievement of the learning goal helps the learner pay attention to the learning process and deploy appropriate cognitive strategies (Bolhuis, 2003). Learner motivation involves learners' goals for the task and their beliefs about the importance and interest of the task. Essentially it concerns learners' reasons for doing a task, that is, the learners' individual answers to the question, "Why am I doing this task?" (Pintrich, 1990). Self Determination Theory (Deci and Ryan, 1985) distinguishes between intrinsic and extrinsic motivation based on the different goals or reasons a learner obtains a goal for completing a task (Ryan and Deci, 2000).

When a learner is inherently interested in a task, the learner is said to be intrinsically motivated (Ryan and Deci, 2000). According to Ryan and Deci, (2000), intrinsic motivation results in high-quality learning and creativity, a goal of modern education (Boekaerts et al., 2006). A learner's interest in a learning task becomes intrinsic when he or she considers the task itself rewarding (Code et al., 2006). Intrinsic motivation is a natural motivational tendency and is a critical element in cognitive, social, and physical development because it is through acting on one's inherent interests that one grows in knowledge and skills (Murphy and Alexander, 2000). On the other hand, when a learner is extrinsically motivated about a particular task, they perform the task to accomplish a goal set by another individual rather than an inherent goal (Murphy and Alexander, 2000). The main difference between the constructs of intrinsic and extrinsic motivation is the perceived control or influence is either external or internal e.g. task instruction (instructor goals) – where the learning goals and objectives are set by the instructor, and learner goals – where the learning goals are set by the learner (Tilstra and McMaster, 2013).

Having goals and objectives is important for learning as they define "where you are headed and how to demonstrate when you have arrived" (Ames, 1992). Goal orientation of learning encapsulates the reasons a learner performs a task and it assists with evaluating the learner's performance on the task (Pintrich 1990). Two major goal orientations exist in the literature: 1) mastery orientation, also called task-goal orientation and learning-goal orientation and 2) performance-goal orientations, also called ego orientation and ability-goal orientation (Ames, 1992). Learners' different goal orientations are key to understanding their varying approaches to regulate their learning in a particular task. Students who adopt a mastery goal orientation are theorized to persist, deeply elaborate study material, and experience enhanced task enjoyment (Dewek, 1998). Students who adopt a performance goal orientation are theorized to process study materials less deeply, experience decreased task enjoyment, and withdraw effort in the face of failure (Dewek, 1998).

As has been mentioned, learners' motivation involves setting learning goals and objectives for the task; which could be done by the learner or by task instruction. According to Smith and Regan (2005), task instructions that include reading objectives are perceived to explicitly describe what the learners should know or be able to do at the completion of instruction. This enables learners, each having unique cognitive conditions, to use the learning goals and objectives specified, to construct personal (metacognitive) standards to decide which information is worthy of attention. While reading and studying, learners use these metacognitive standards to guide search and selection processes to locate information that merits attention (Winne and Hadwin, 1998).

The inclusion of the reasons (learning goal) why a learner is pursuing a task also allows for the integration of the achievement motivation into the model of self-regulated learning (Pintrich and Schunk, 1996). Intelligent self-regulation requires that the learner has in mind some goals to be achieved, against which performance can be compared and assessed. The feedback from the learner's assessment gives useful information on the learner's present state of learning and performance in relation to the learning goals and objectives (Smith and Regan, 2005). Therefore, in our approach to examining text marking as an effective metacognitive reading strategy, the experimental design in this study entailed a reading task in a self-regulated learning setting, where learning goals (reading objective) for the task were specified using task instructions we adopted the inclusion of learning goals — task instructions.

In the next section, we discuss how we utilized the metacognitive activities a learner engages in while reading as a preference elicitation method, to guide the recommendation of relevant learning materials to facilitate personalized learning.

RECOMMENDER SYSTEMS

In general, recommender systems provide suggestions of objects to a user, and they are widely used in the e-commerce and e-learning domains. In the e-commerce domain, recommendation is a popular personalization technology where the objects for recommendation are products (such as movies, books) and the users are the customers. In the e-learning domain however, the objects for recommendation are learning materials, and the users are the learners or students. The main objective of the recommender systems, regardless of the domain in which it is applied, is to predict objects that are of interest or relevant to a user. Recommender systems rely heavily on information related to a given domain. The dependency restricts the possibility of applying the recommendation strategy used in one domain to another. For example, personalized recommendation in the e-commerce setting is based on what other users like/ratings, while in the e-learning/TEL setting, it is argued that to achieve personalized recommendations, the recommendation tool should also take into account other features peculiar to each learner, such as: current learning goal, prior knowledge, and other learner characteristics (Drachsler, 2009).

The popular approaches in recommender systems for e-commerce are collaborative filtering, content-based method, knowledge-based method and hybrid methods (Syed, 2018), while data mining, concept maps, fuzzy logic, and ontologies are the common approaches that have been used in TEL settings. We review these recommendation methods briefly. The collaborative filtering (CF) method is the most popular technique used in recommender systems. It is often regarded as a social-based approach which makes use of the collective behaviour of a collection of learners to make recommendation. CF based algorithms provide recommendations or predictions based on the opinions of other like-minded users. Recommendation in CF entails the analysis of the relationship between users and the interdependencies among products to identify new user-item associations (Koren, 2008). Content based techniques, also referred to as information-based approaches, make use of the information about individual users or items for recommendation. The basic approach of content-based filtering is to compare the content of already consumed items (e.g., a list of news articles) with new items that can potentially be recommended to the user, i.e., to find items that are similar to those already consumed (positively rated) by the user. Items are recommended to users by associating the users to items with matching/similar attributes. The knowledge based approach does not rely on the user ratings and item descriptions, rather it makes use of deep semantic knowledge about the items to make recommendations. This approach aggregates the knowledge about the users and items then applies this knowledge to generate recommendations (Felfernig et al., 2014). The semantic information provided for the items describes the item in finer detail that allows the information to be exploited in a different way. Thus, knowledge-based recommender systems generate recommendations based on matching between users needs, preferences and set of items available (Felfernig et al., 2014). The motivation for hybrid recommendation systems is the opportunity to achieve greater accuracy from the combination of two or more recommendation approaches. For example, a hybrid system that combines two recommendation approaches e.g. content-based technique and collaborative filtering technique, makes recommendation by leveraging the benefits of both techniques.

Recommender Systems for Learning

In TEL settings however, the recommendations provided are aimed at achieving personalized learning — personalized learning recommender systems. The basic idea behind personalized learning recommendation is the need to provide recommendations that meet the specific learning needs and requirements of the learner to enhance the learning experience. The development of personalized learning recommender systems of necessity includes a *learner model* which is used to obtain/infer information about the learner. The learner profile is used to capture information about the learner's characteristics such as the learning goal, learning style, prior knowledge, and the information obtained is used to guide recommendation. As aforementioned, data (web) mining, concept maps, fuzzy logic, and ontology based recommendation are some of the preference elicitation methods that have been deployed to capture information about the learner, and build a learner model, in order to provide personalized learning recommendations.

The use of web mining techniques to build an agent that could recommend online learning resources, activities or shortcuts based on learners' Web navigation history can be used to improve learning as well as provide personalized recommendations (Zaiane, 2002). This can be achieved by using Web usage mining, which performs mining on web data, particularly data stored in logs managed by the web servers. The web log provides raw traces of the learners' navigation and activities on the website (Zaiane, 2002). These information is then used to build a learner models, and to generate recommendations. In the field of recommender systems for TEL, concept maps have been used to capture the learner model, as well as the domain (learning resources). Based on users concept knowledge demonstrated through automated evaluation an approximation of their knowledge is determined. Therefore, recommendation is made by evaluating the similarity between the learner's knowledge to the domain resource (typically both represented as concept maps), and based on the misconceptions and knowledge gaps identified, the system provides recommendations.

The fuzzy logic approach makes use of fuzzy knowledge extraction models to extract personalized recommendation knowledge by discovering effective learning paths from past learning experiences. As learners explore their learning performances along learning paths characterized by specific learning contexts, the trail marks of their explorations can then be used to discover effective learning paths for them with specific learning styles and competency. A learner model is thereafter described in terms of competency and learning style; symbolized using a fuzzy set theory. The recommendation task in this approach is modelled as finding best learning paths for different types of learners in different knowledge subspaces, consisting of nodes and edges, dictating the learning paths of learners with particular learning contexts, indexed by competency levels and learning characteristics. Ontologies, a semantic Web technology facilitates knowledge sharing, reuse, communication, collaboration and construction of knowledge rich and intensive systems (Syed, 2018), and have been adapted in the design of recommender systems for TEL in a number of ways: to model the learner's profile, to structure learning materials, to denote the semantic relationship between learning materials, among others. The advantage of the ontology based method is that it is based on a well-established mechanism that makes the information machine-interpretable and allows syntactic and semantic interoperability among web applications. Using these infrastructures to represent the components of a recommender system (domain, learner model) makes it easier to retrieve resources as well as matching or correlating users to items and similar users, this is because the properties of a component are described through metadata and not on its actual content.

PERSONALIZED LEARNING RECOMMENDATIONS: METACOGNITIVE ACTIVITIES

To facilitate personalized learning, enhance learning experiences, as well as encourage metacognitive reading activities, in this research, we developed a recommender system that provides these features to the learner. The recommender system developed is intended to assist learners' select appropriate textual documents for task-oriented reading. Task-oriented reading is an activity where an individual reads to meet a goal (McCrudden and Schraw, 2007), which may be provided by an instructor or a self-directed reading goal. Such readings may involve multiple documents. Task-oriented reading of multiple documents therefore requires the ability to search for and identify relevant resources that facilitate the completion of the reading task. In this context, a recommender system is considered a resourceful tool that could be used to identify relevant documents from a large pool of documents. A recommender system for educational purposes therefore should be tailored to support the learners' information seeking needs as well as enhance the learner's learning experience.

Recommendation Process

The process of recommendation incorporates the metacognitive activities of the learner to provide personalized recommendations that aims to address the learner's information seeking needs which may be captured during the process of reading. We refer to the learners' interaction with a learning material as metacognitive activities. During a reading session, learner's interact with the reading material in a number of ways, which may include marking a portion of the text (create highlights), make notes. These interactions/meta-cognitive activities serve as the user model and preference elicitation method (input) to the recommender system, and is a novel method/input mechanism for recommendations. The use of the learners' metacognitive activities as input to the recommender system is intended to replace search queries. Typically, the information seeking needs of a learner are expressed using a search query in a search engine. However, search queries do not always return relevant information, due to reasons such as poor queries and natural language ambiguities (Batista, 2007). Therefore, a more cognitive approach to identifying the learners' information needs can be achieved by examining the interactions the learner engages in with the learning materials. The metacognitive activities of the learner (e.g. highlights, notes, comments) usually contain more information than search queries text, this gives the learner the freedom to express his/her information seeking needs in different ways without limitations.

To observe how learner's interact with a learning material while reading in a natural setting, we conducted a pilot study involving 10 graduate students. The pilot study required that the participants engage in a number of metacognitive reading activities (text marking, tagging and creating notes). The results of the study indicated that learners may create multiple (more than one) interactions that span multiple topics. Therefore, we realized that using the popular standard information retrieval methods (e.g. likelihood model) for recommendation in this situation may not be adequate to address the information seeking needs of the learners covered in the topically different interactions created. To address the different topical needs that may be contained in the learner-generated metacognitive activities, we deployed a probabilistic topic modelling approach for document retrieval and recommendation. Probabilistic topic modelling involves statistical methods that are used to analyze and annotate large collections of documents based on the topical structure of the collection. By deploying probabilistic topic modelling for document retrieval and recommendation, the recommendation process leverages the capability of topic models to discover the latent topics contained in a collection of documents, as well as the topics contained in the metacognitive activities of the learners. This enables the recommender system to provide recommendations to the learner based on the topic similarity of their metacognitive activities to documents in the collection. Thus, the recommender system is robust enough to recommend a range of topically diverse documents that are based on the topics contained in the learners' metacognitive activities, which are reflective and relevant to the learners' information seeking needs.

Latent Dirichlet Allocation (Blei et al., 2003), a widely used approach to building topic models is based on a formal generative model of documents and has been extensively studied considering its feasibility and effectiveness for information retrieval. The experiments by Wei and Croft (2006); Yi and Allan (2009) compared a number of probabilistic topic modelling approaches for information retrieval. The report of the studies confirmed that topic models are effective for document smoothing, indexing and retrieval, and more rigorous topic models such as Latent Dirichlet Allocation provide gains over other information retrieval methods such as the likelihood model. The Latent Dirichlet Indexing (LDI) model developed by Wang et al., (2010) leverages the Latent Dirichlet Allocation (LDA) approach for representing documents to build a model specifically for document indexing and retrieval. Specifically, the LDI model provides a representation of documents and queries in a topic space, where the topics can be seen as index terms for indexing. The LDI model was observed by Wang et al., (2010) to perform better than the LDA model and other topic modelling methods for document indexing and retrieval tasks. Therefore, in this study we deployed the LDI model in the recommendation process for the retrieval of fine-grained topically relevant documents that are tailored to the learner's information seeking needs.

We also asked the participants of the pilot study to evaluate the documents retrieved based on the LDI model against documents retrieved using the standard query likelihood retrieval model. 80% of the participants reported that the sets of documents retrieved using the LDI model were better in terms of providing finer grained, and topically related articles. For an example to compare recommendations based on a user's query and the default document retrieval method (likelihood model) and our proposed approach – recommendation based on the learners' metacognitive activities and the LDI model for document retrieval, given a reading task to "write an essay on the cost and environmental implications of the Massey tunnel." Assuming the user types the following query on a search engine: "cost and environmental implication of the Massey tunnel." The likelihood document retrieval model would provide documents that discuss both the cost and environmental issues (which may not exist or be adequate to complete the task). However, our proposed approach, the learner isn't required to type in a search query but rather interact naturally with the learning material e.g. by creating highlights (text marking). Assuming the learner creates the following highlights: "financial information and detailed cost estimates of proposed bridge released", "conduct an independent technical review of the bridge." The system designed takes all the learner's highlights and treats them as a pseudo document. Then, it infers the topics contained in the pseudo document, and identifies two topics: "cost information of the Massey Tunnel" and "environmental assessment of the Massey tunnel." Based on the topics inferred, it recommends to the learner documents that discusses each of the topics. Therefore, our proposed methodology for recommendation first, removes the extra task the learner has to perform by not only typing a search query but also identifying the right search query that would give relevant documents (this may take several rounds of refining the search query). Second, using topic models for document retrieval makes it possible to provide multiple but finer grained topically related documents that would be useful to complete the reading task.

Document Indexing and Retrieval

Document Retrieval refers to the computerized process of producing a list of documents that are relevant to an inquirer's request by comparing the user's request to an automatically produced index of the textual content of documents in the system (Liddy, 2005). A number of theoretical models have been developed and used for document retrieval such as Boolean, Vector Space, Probabilistic, and Language Modelling models. These models match the terms in a user query to the index terms that represent a document and rank the matched documents for retrieval. Document Indexing (DI) is considered a crucial technique to retrieve significant information for users (Choi and Lee, 2010). Using DI, text documents are converted into index terms or document features that can be trivially analyzed by computers. With an appropriate ranking function or retrieval model, and has been shown to be effective for document retrieval (Croft et al., 2010).

Indexing and retrieval using probabilistic concept models are based on the assumption that the concepts are distributed differently in relevant and non-relevant documents. Latent Dirichlet Allocation (Blei et al., 2003), a widely used approach to building topic models is based on a formal generative model of documents and has been extensively studied considering its feasibility and effectiveness for information retrieval. The Latent Dirichlet Allocation (LDA) model addresses the topic-based structural analysis of corpora, and thus it can be regarded as a model for topic search. Given that LDA models documents as a mixture of topics, Wang et al., (2010) developed a method — Indexing by Latent Dirichlet Allocation (LDI) — that leverages the topic modelling approach for representing documents in a topic space; where the topics can be seen as index terms for indexing. We would briefly describe the LDI method in the section below.

The LDI Model

For document indexing and retrieval purposes, the LDI method defines each word in a document as well as the documents in a corpora in the topic space. This is achieved in two steps:

1. In the first step, the LDI method computes the probability of a topic given a word. The LDI method directly uses the β matrix of the LDA model to construct explicit document representations associated with topics. The conditional probability β_{jk} in LDA is considered as the selection probability of the word given a topic (concept) z^k; which represents the probability of a word w^j given a specific topic and is used to identify words that are associated with a topic. The probability of a word corresponding to a topic is given as:

$$w_j^k = \frac{\beta_{jk}}{\sum_{h=1}^{K} \beta_{jh}} \tag{1}$$

2. The next step computes the probability of a topic given a document. Here also, the LDI method assumes that the conditional probability $p(z^k|w^j, d_i = p(z^k|w^j)$. This assumption is based on the LDA assumption that there is a fixed number of underlying topics that are used to generate the words in documents (Croft et al., 2010). In other words, it is assumed that the words in topic space do not depend on which document it is used in, but on the topic it is generated from. The probability of a topic z^k, given a document d^i is expressed as:

$$p(w^j|d_i) = \frac{\sum_{w^j \in d_i} W_j^k \eta_{ij}}{N_{di}} \tag{2}$$

In general, a document includes various words that are used to explain key topics in the document. The definition of document probability in equation (2) captures the topical features of words in the document. This definition is distinguished from the usual definition of the probability of a document in LDA, which assumes that document probability is the same as the probability of the simultaneous occurrence of all words used in the document. The new definition overcomes the difficulty that is associated with the latter definition in which the probability of a document considerably depends on the length of the document. If topics are regarded as index terms, document representation in the topic space can therefore be utilized for automatic document indexing (Wang et al., 2010).

Similarity Between Document and Query

Using equation (1) and (2), each term in a document can be represented in the topic space $W_j^k = \{W_j^1, W_j^2, \dots, W_j^K\}$. Given a query, to determine the documents that are most relevant to the query, the LDI method also computes the similarity between document and query. The query is considered as a pseudo-document that contains a set of query terms $Q = \{q_1, q_2, \dots, q_L\}$. Similar to equation (1), the probability vector of the query with respect to the *kth* topic can be defined in the concept space as:

$$Q^k \approxeq \frac{\sum_{q_j \in Q} p(z^k|q_j)}{L} \tag{3}$$

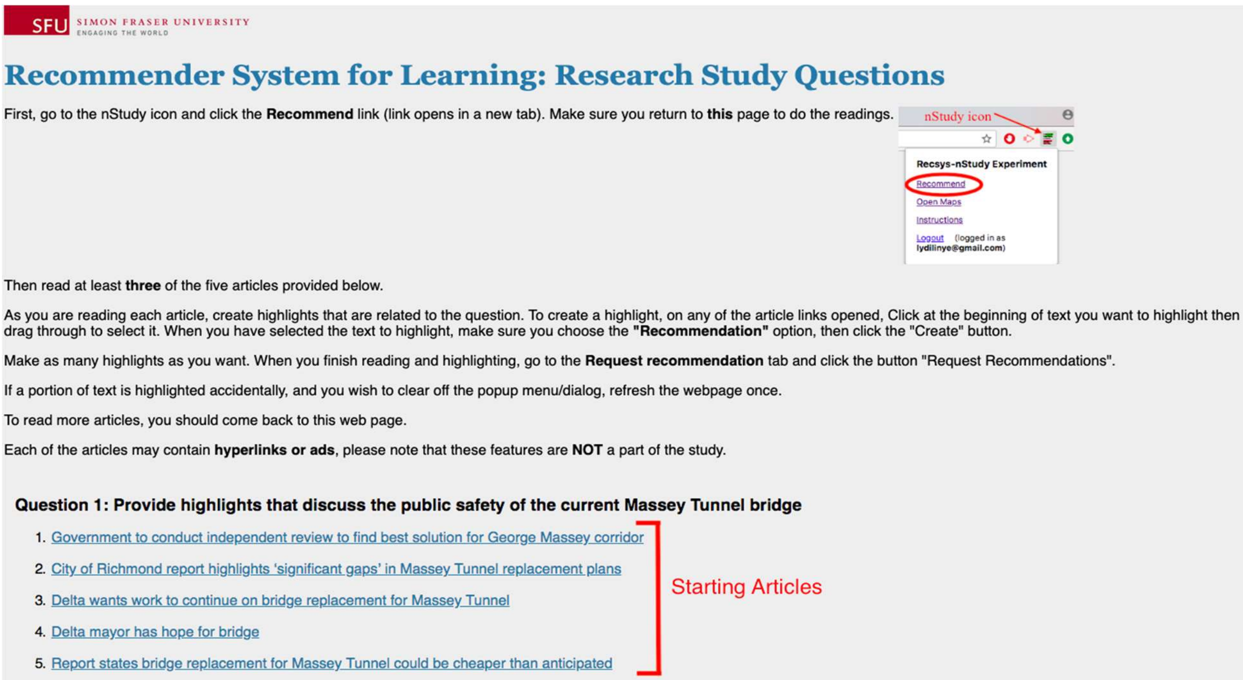
and the similarity between query Q and document d_s is measured by:

$$p(d_s, Q) = \vec{D_s} \cdot \vec{Q} \approxeq \vec{\hat{D}_s} \cdot \vec{\hat{Q}} \tag{4}$$

where $\vec{Q} = \{Q^1, Q^2, \dots, Q^K\}$ in the topic space. Representing a query as a probability vector is made possible owing to the definition of the document probability vector in equation (1). The probability vector represents the characteristics of the words, documents, and queries in the topic space. An advantage of the LDI method is that an unseen training query can be treated coherently as a document in the training set (Wang et al., 2010). As with the LDA model, the size of topic space K plays an important role in the LDI method also.

In LDA, the topic size K determines the degree of abstraction of information, i.e. the larger the value K is, the finer is the segmentation of information.

FIGURE 1
INSTRUCTIONS, NSTUDY ICON AND THE STARTING ARTICLES OF THE USER STUDY



The Learning Platform

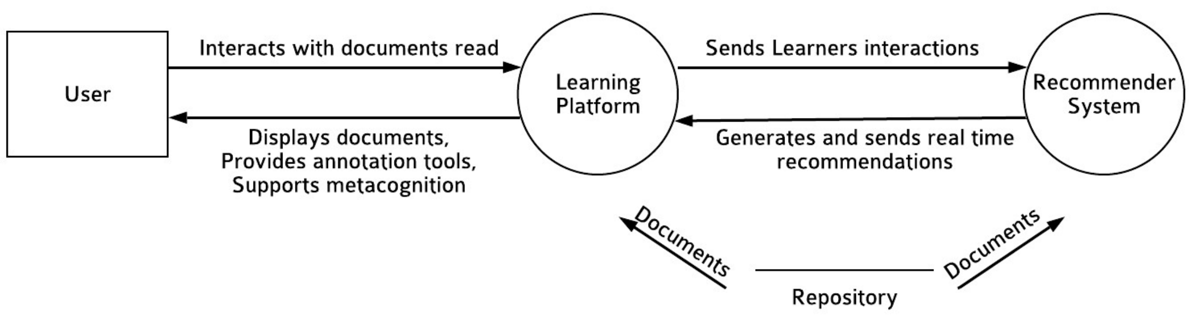
The learning platform that we used is nStudy (Beaudoin and Winne, 2009). nStudy is an online tool that supports learning and research. nStudy provides the annotation tools that allows learners interact with an online document as they would with a paper version. The annotation tools allow the learners record, organize, view the documents they read. Some of the annotation tools that nStudy provides are highlights (text marking), tags, notes. nStudy an application developed at Simon Fraser University is being used by students at the institution, which makes it easier for us to do our studies. However, any other learning platform that supports the metacognitive reading activities investigated in this study could be used. For this study, the annotation tools supported by nStudy that were used are the highlights and tags. The nStudy interface is used to display the reading task, task instructions, and the participants are able to read the articles as well as make annotations on the articles using the interface. As a learner uses nStudy, the software records very fine grained time stamps of all the activities performed by the learner, such as bookmarking the web sites visited, records the notes created, as well as the information operated on (e.g. text highlighted, tags). To obtain data on the learners' interaction, the recommender system developed is integrated with nStudy. As a learner reads articles, make highlights or create tags on nStudy, the details of the portion of text highlighted and/or tag created are sent to the recommender system in real time. Based on the meta-cognitive activities of the learner the recommender system receives, it is able to make personalized recommendations that are tailored to the learner's interests. In this case, the feedback obtained from the learner serves as a prompt (search query) that signals to the recommender system the kind of items the learner may be interested in.

Description of the System

The recommender system was designed as a plug-in to be integrated to the nStudy learning platform (and could be extended to other online platforms that support metacognitive reading activities). To use the system, the learner is first required to either create an account or sign in. This step is important to create a record of all the activities the learner engages in. Thereafter the learner commences searching for documents, reading and interacting with the documents read. In the case of the user study we conducted, after the participants creates an account and/or signs in, the demographics questionnaire is administered online immediately. Upon completion of the questionnaire, a web page containing a brief instruction on what to do, as well as the list of starting articles (see Figure 1) for the task is displayed. The starting articles (which were chosen randomly) are the initial articles the learner reads and interacts with to commence a reading session. As the learner reads the articles, they perform metacognitive reading activities (text marking, tags). There may be various reasons a learner creates a highlight. The use of tags could be used to specify the reason. This study adopts the use of tags, however, the set of tags were limited to two. This is because to complete the educational task of the study, learners had to put together an ensemble of highlights in lieu of writing an actual essay. Therefore, the tags were used to distinguish between the highlights created to complete the task and otherwise (for recommendation).

Upon creating at least one highlight, and the learner would like to receive more articles (new recommendations), the recommend plug-in is opened and the request recommendation button is clicked. The new list of recommended articles is opened on a new tab which contains articles related to the topics/themes inferred from the highlights the learner had made. The learner could go through the process of reading-highlighting-request recommendation for any number of time and when satisfied with the highlights created to complete the task, the feedback questionnaire is administered for the learner's evaluation of the system. Figure 2 below shows pictorial description of the system and the data flow within the system.

FIGURE 2
PICTORIAL DESCRIPTION OF THE SYSTEM AND DATA FLOW



User Study Procedure

There has been an increased interest in more user-centred evaluation metrics for recommender systems such as those mentioned in (McNee et al., 2006a). Therefore, a user study was conducted to include a user-based evaluation of the quality of the recommender system and also to attempt to answer the research questions of the study. The participants were 49 undergraduate students, 27 females and 22 males with various disciplinary majors attending a university in Western Canada. Ages ranged from 18 to 26 years (M =21, SD=2.67). All participants were recruited via an advertisement posted in a busy spot on campus.

There are two treatment conditions involved in the user study: (a) random recommendation, and (b) experimental recommendation. Participants would be randomly assigned to one of the two treatment groups. Both groups received recommendations from the collection of articles used in the study. However, the random recommendation group received randomly selected recommendations using a random number generator module, while the experimental recommendation group received recommendations based on this study proposed methodology (LDI model and the learners' meta-cognitive activities).

Two questionnaires were included in the study, a demographics questionnaire, used to obtain some personal information of the participants (e.g. domain knowledge), and a feedback questionnaire where the participants are asked to provide their perception about various aspects of the recommender system. The demographics questionnaire is presented before the participant begin the study task, while the feedback questionnaire is administered after the participant completes the task. The Likert scale is used to design questions in the feedback questionnaire, and participants are expected to select a rating on a scale that ranges from one extreme to another: "strongly agree" to "strongly disagree."

The educational task for the user study required that the participants complete two essay-like questions. Participants were not required to write out actual essays but rather provide an ensemble of highlights (marked texts) that would be suitable to answer the questions. For reasons such as different writing capabilities of learners in general, we decided not to ask the learner to write actual essays, but to put together highlights from the (recommended) articles they read that would be adequate to complete the tasks. Before commencing the task, detailed instructions were specified, providing a step-by-step guide on what is expected, and how to complete the task. The instructions were carefully stated to not interfere with the natural way the learners behave when studying, to be able to simulate and obtain best results that depict the 'true' way learners interact with learning materials for a task-oriented activity. To begin the reading process for the task, the participants were presented with a list of five randomly selected articles from the collection of articles (we refer to these articles as the entry articles). Only the entry articles titles are presented at this point, and the titles are clickable links to the corresponding web pages. The participants decide on which of the entry articles to commence reading, and when to create highlights.

The task for the study is about the George Massey tunnel. To obtain a collection of news articles on the George Massey tunnel, we crawled 16 online news websites between August 8 and September 30, 2017. A total of 95 articles that discuss various issues on the George Massey tunnel replacement project were obtained. The collection of articles had an average of four paragraphs, had a title, and the content of the news article was structured. The Latent Dirichlet Allocation (LDA) model was used to infer the topics in the collection of news articles. A Java-based package of the LDA model, MALLET (McCallum, 2002), was used. Nine distinct topics were identified. The number of topics were determined experimentally, by trying out other values and examining the topics output. The output of LDA model was used for the document retrieval phase of the recommendation task using the LDI model.

EVALUATION

The standard evaluation measures used to assess recommender systems can be split into three categories: online metrics, offline metrics and user feedback. The online metrics assess how the learner interacts with the recommendation. For example, the metric clickthrough rate would be used to measure the number of articles the learner clicks/reads from the list of recommended articles, session success rate would be used to measure the number of articles the learner operated on for the completion of the task. The offline metrics measures the relevance of the recommended articles to the information needs of the learner, such as precision, recall, F-score. The user's feedback on the recommender system is obtained by administering questionnaires at the end of a user study session. In the context of recommendation systems, recommending top-N items to the user is a widely used approach. Therefore, similar to modern information systems, a more useful metric is precision and recall metrics of the first N items instead of all the items. Thus the notion of precision and recall at k where k is a user definable integer that is set by the user to match the top-N recommendations objective; where precision is the proportion of recommendations that are good recommendations, and recall is the proportion of good recommendations that appear in top recommendations. Computing precision and recall values requires a gold standard or ground truth judgment of relevance document collection (e.g. TREC), which contains large number of queries and binary classification of documents that are relevant or non-relevant with respect to the query.

Information retrieval/filtering methods (including recommender systems) typically map a query to a ranked list of retrieved documents, however, our approach to recommendation maps multiple "queries" (expressed in the learner's metacognitive activities) to an ordered list of retrieved articles. Therefore, the standard offline metrics (precision, recall) as well as the gold standard data collections are not suitable for evaluating the recommender system. We therefore limit our evaluation to online metrics and user feedback.

These metrics have been combined into a user-centric framework for evaluating recommender systems by Knijnenburg et al., (2012). The framework provides insight into the relationships between the general concepts that play a role in the user experience of recommender systems and consists of six interrelated conceptual components: (a) Objective System Analysis: The Objective System Aspects (OSAs) are the aspects of the system that are to be evaluated such as the algorithm, input mechanism, and output/presentation mechanism, (b) Subjective System Analysis: The Subjective System Analysis (SSAs) are regarded as the mediating variables that attempt to explain the effects of the OSAs on the user experience and interaction, (c) User Experience: The user experience (EXP) are the users' self evaluations of the effectiveness of the different aspects of the recommender system such as the system's usefulness, appropriateness of the recommended items, (d) User Interaction: The user interaction (INT) factors objectively measure how the user interacted with the system, (e, f) Personal and Situational Characteristics: The personal characteristics (PCs) and situational characteristics (SCs) of a user are factors that can influence the users' evaluation of the SSAs, EXP and INT with the recommender system. PCs such as domain knowledge, gender have been shown to affect SSA measures, also SCs (e.g. trust in technology) have been shown to effect the INT variables (Knijnenburg et al., 2012).

Data Sources

To provide answers to the research questions and hypotheses of the study, three data sources from (and about) the user are used and analyzed.

1. Logged data: The logged data comprises the observable behaviour and activities of the learner during the study. The behaviour of the learner that would be analyzed in this study are: the number of recommended articles the participant clicks, and the number of articles the participant operated on (e.g. creates highlights, notes, tags). Also, the content of the metacognitive activities of the participants would be used for data analysis (e.g. the text highlighted, the text of the tag created). nStudy, the learning platform being used for the study records very fine grained time stamps of all the activities performed by the learner. Therefore, the logged data nStudy records for each participant would be used.
2. Questionnaires: Before the reading activities the participants are administered a demographics questionnaire. Also, upon completion of the tasks, another (feedback) questionnaire is administered, used to obtain the participant's feedback about the recommender system. Both questionnaires are administered online and are intended to obtain some personal information of the participants as well as to measure each participant's experience and a number of subjective analysis of the recommender system (e.g perceived recommender quality).

Variables for Analysis

The independent variable and dependent variables measured by the questionnaire are outlined below:

A. Independent Variable: The independent variable is the objective aspect of the system (the methodology of the recommender system) which would be manipulated in the different experimental conditions, and allow us to measure the differences in outcomes between the conditions.

    System's Methodology: Using the variations in the experimental conditions in this study, we seek to investigate the effect of the recommender system's methodology: (a) preference elicitation method – learners' highlights (b) document retrieval method – LDI model, on the dependent variables discussed below

B. Dependent Variables: The dependent variables are intended to measure the user interaction (INT) and user experience (EXP). A combination of the observed behaviour of the participants with the recommendations, and the subjective analysis of the system from the users' point of view (obtained from the post-experiment questionnaire) would be used. As stated by

Knijnenburg et al., (2012) it may not be possible to explain the effects of the independent variables on the dependent variables directly. For example, if it is observed that participants are more satisfied or behave differently between experimental conditions, these observations may need to be justified (Knijnenburg et al., 2010). The authors have shown that the user experience and user interaction with a system may be explained using a number of mediating variables (SSAs), which could be analyzed to measure the effect of the different experimental conditions (manipulation of the system) on the user experience and user interaction. The mediating variables explain how and why the effects come about. The mediating variables can be used to test the hypothesized effect of the independent variables (does the objective analysis of the system correlate with the subjective analysis of the system) and also provide explanations for the effects between experimental conditions. The mediating variables in the study are:

> Perceived recommendation quality: Is a subjective measure of the relevance of the recommendations the system provides. It measures the participants' perception of the quality of the recommendations received, for the different methodologies used in the experimental conditions. The participants' perceptions of the recommendation quality may be useful in predicting the effects of the recommender system's objective aspects on the user experience and user interaction.
>
> Perceived recommendation accuracy: Measures subjectively how the system is able to provide recommendations (using the LDI model) that fit the information seeking needs of the participants, as well as recommend appropriate articles for the completion of the educational task. Similar to the perceived recommendation quality variable, perceived recommendation accuracy can be used to test the effects on the independent variables, dependent variables as well as the study outcome. In this case, perceived recommendation accuracy can also be used to predict the effects of the recommender system's aspects on the user interactions: number of recommended articles clicked, number of recommended articles operated on.
> Preferred elicitation method: Measures the participants' perceptions on the preference elicitation method used. This variable is also assumed to be also useful in investigating the effects of the system's methodology on the users' experience and interaction. The variables to measure user experience are obtained from the questionnaire, they are:
>
> - Perceived system effectiveness
> - Recommendation choice satisfaction
> - Effort to use the system

The variables to measure user interaction are obtained from the logged data of the participants' engagements with the recommendations, they include:

- Number of recommended articles clicked
- Number of recommended articles operated on

As aforementioned, a number of other variables (commonly referred to as personal and situational characteristics) have been shown to affect the users' subjective analysis of the system as well as the user experience (Knijnenburg et al., 2012). These variables are obtained from the questionnaire administered to the participants of the study.

- Domain knowledge: Measures how the prior knowledge of the participant influences perceived recommendation accuracy, perceived recommendation quality and user experience.
- Gender: Investigates whether gender as a PC influences the user perception of the recommendation accuracy, recommendation quality, user interaction and user experience.

- Trust in technology: Measures how issues relating to the participants' trust in technology influences perceived recommendation accuracy, perceived recommendation quality and user experience.
- Privacy concerns: Measures how issues relating to the participants' privacy with using the system and/or providing data to the system influences perceived recommendation accuracy, perceived recommendation quality and user experience.

Research Questions and Hypotheses

Based on the proposed methodology for recommendation of textual documents, we seek to investigate and address the following research questions in the user study:

1. Is the learner-generated highlight appropriate data for the learner model, and suitable as a preference elicitation method for recommendation? The use of highlights to guide recommendation is novel. Therefore, we seek to determine if it is an appropriate input mechanism for recommendation. To answer this question, we hypothesize the following:
   H1.1: There is a significant difference in the preference elicitation method between the two group conditions.
   H1.2: The preference elicitation method has a positive effect on the user experience.
2. What components of the framework affect the user experience? We seek to examine the effects of the subjective system aspects, personal characteristics and situational characteristics of the evaluation framework on the user experience. To answer this question, the effects of these components are examined individually.
   2.1: Subjective system aspects on user experience
   2.2: Personal characteristics on the user perception and user experience
   2.3: Situational Characteristics on the user perception and user experience.
3. What components of the framework affect the user interaction? This research questions examine the effect(s) of the preference elicitation methods, user experience, personal characteristics, and situational characteristics on the user interaction. To answer the question, the effects of these components are examined individually.
   3.1: Effects of the user experience on user interaction.
   3.2: Effects of personal and situational characteristics on user interaction.
   3.3: Effects of the preference elicitation method on user interaction.

RESULTS AND FINDINGS

This research involved the design and development of a recommender system to support TEL using a novel feature – the learners' highlights, a metacognitive reading activity – to guide recommendation. The main questions investigated are: (1) Is the learner-generated highlight appropriate data for the learner model and preference elicitation method for recommendation? Which entails investigating three components: subjective system aspects, personal characteristics and situational characteristics (2) What components of the framework affect the user experience? (3) What components of the framework affect the user interaction? Also entails examining four components: user experience, preference elicitation method, personal characteristics and situational characteristics. The post-experiment questionnaire contained thirty questions targeted at eight categories: perceived recommendation quality, perceived recommendation accuracy, preferred recommendation input method, perceived system effectiveness, recommendation choice satisfaction, perceived effort to use the system, personal characteristics, and situational characteristics. To determine if the questions fit the categories intended, exploratory factor analysis with Varimax rotation was performed to extract factors from the observed variables.

To test the internal consistency of the items, each of the categories, Cronbach's alpha reliability test was performed, which measures how closely related the set of items are as a group. Due to space limitations, Table 1 shows a sample of the factor analysis loadings for the questions of the questionnaire, and Appendix A contains the complete table. The results of Cronbach's alpha reliability tests reveal that the items in the categories/factors are internally consistent; where a reliability coefficient of 0.70 or higher is considered "acceptable." To answer the research questions and test the hypotheses of the study, we adopted a pragmatic procedure which entails computing independent sample T-test (statistics), p-value (significance), effect size tests (Cohen's d), and regression analysis for each effect. We discuss the results and findings in the next sections.

Is the Learner-Generated Highlight Appropriate Data for the Learner Model, and Suitable as a Preference Elicitation Method for Recommendation?

Given that the use of highlights (learners' metacognitive activities) to guide recommendation is novel, this research question therefore attempts to investigate if it is an appropriate input mechanism for recommendation. It is important to note here that two types of highlights/ text marking was used in the study: highlights for recommendation and highlights to answer the task/question.

TABLE 1
SAMPLE OF THE CONSTRUCTS AND THEIR MEASUREMENT

Question	Variable	Loading
Recommendation Quality (Cronbach's alpha: 0.92)		
I liked the articles recommended	like_articles	0.848
The system provided valuable recommendations	valuable_articles	0.861
The system had too many irrelevant recommendations	too_many_irrelevant_articles	0.792
I didn't like any of the recommended articles	didn't_like_articles	0.804
Recommendation Accuracy (Cronbach's alpha: 0.879)		
The articles were well chosen based on my highlights	well_chosen_articles	0.811
The recommended articles were relevant to completing the task	relevant_articles	0.893
I would give most of the articles recommended a high rating	high_rating_articles	0.846
The list of recommended articles was appealing	articles_appealing	0.799
Preferred Elicitation Method (Cronbach's alpha: 0.813)		
I prefer to use highlights for recommendation	prefer_highlighting	0.823
I would have preferred typing search queries for recommendation	prefer_typing	0.914

Recommendation System Effectiveness (Cronbach's alpha: 0.905)		
I would recommend the system to others	recommend_system	0.823
The system made me aware of my highlights	aware_of_highlights	0.742
I can find better articles using the recommender system	better_articles_with_system	0.895
I can find better articles without the recommender system	better_articles_without_system	0.806
Recommendation Choice Satisfaction (Cronbach's alpha: 0.798)		
I enjoyed reading the articles I selected	enjoyed_reading_articles	0.938
The articles were appropriate for the task	task_appropriate_articles	0.892
The chosen articles fit my preference	articles_fit_preference	0.837
The articles I read were a waste of my time	articles_waste_of_time	0.826

To differentiate between the highlight types, after the learner selects a portion of text to highlight, a pop-up menu containing two tag options is opened. The learner then labels the highlight with the appropriate tag as intended. The set of highlights analyzed to answer this research question are the highlights for recommendation. The participants received no training on how to create highlights using the learning platform nStudy, and were not restricted on the number of highlights to be created nor the number of times they could request for recommendations. From the data analyzed, for both group conditions (experimental group: Group A, and control group: Group B), the average number of highlights created was *34.76* for participants in Group A, and *11.52* for participants in Group B. The average number of words a highlight consisted of *11.8* words. The participants in Group A requested recommendation on average *2.7* times while participants in Group B requested for recommendations an average of *5.3* times. Further analysis on the content and features of the subsequent highlights participants made showed that the highlights got "better" after each iteration of recommendation requested. To judge what a good highlight is, we came up with three qualities: (a) the highlight should contain keywords that are related to task (b) the highlights are among the pre-identified texts in the articles that the researcher had identified to generate optimal recommendations to complete the task (c) the highlight contained less than 15 words and does not span multiple sentences. The threshold for the number of words is based on the assumption that search queries typed contains an average of *8* words and do not exceed *15* words (Hurn, 2009).

The responses to the feedback questionnaire also showed that *92.3%* of the participants in Group A reported to prefer the use of highlights to guide recommendations, while *51.8%* of the participants in Group B noted their preference to use search queries to guide recommendation. To explain the difference in the preference elicitation method between the two groups, as well as examine the effect (if any) on the user experience, and user interaction, a number of hypotheses were tested (discussed below) using independent sample t-test, regression analysis and correlation tests. It is important to note that based on our assumptions that the participants' (being undergraduate students) are familiar with using search queries, and experience some challenges with search queries, the experimental design of the study did not include a treatment condition to specifically test the use of search queries in comparison to highlighting. Therefore the outcome of the results may not validate the participants 'preference for using highlights vs. typing a search query to guide recommendation.

TABLE 2
MEAN RESPONSES, T-TEST RESULTS OF THE PREFERENCE ELICITATION METHOD VARIABLES

Variable	Group A Mean Responses	Group B Mean Responses	T-Values
prefer_highlighting	4.58	2.65	t(47) = 3.57 p < 0.001 d = 1.540
prefer_typing	2.28	3.86	t(47) = -1.75 p = 0.006 d = 1.332

H1.1: *There is a significant difference in the preference elicitation method between the two group conditions.*

This hypothesis tests whether there is a significant difference between the means of the two groups. Two items were used to collect the participants preferences. Table 2 shows the mean responses to the items measuring this concept. Results of the t-test also show that this difference is significant with a large effect size for both variables prefer_highlighting: *[t(47) = 3.57, p < .001, d = 1.54]* and prefer_typing: [*t(47) = -1.75, p = .006, d = 1.33]*. Therefore, we accept the hypothesis that there is a significant difference in the preference elicitation method between the 2 group conditions; where participants in the experimental group (Group A) had a greater preference for the use of highlights to guide recommendation, and participants in the control group (Group B) had a greater preference for using search queries to guide recommendations.

A possible explanation for the results obtained could be due to the (perceived) quality and/or accuracy of the recommendations received. Group B participants received random recommendations, which implies that the highlights they created weren't taken into account nor used in the recommendation generation process, and otherwise for participants in Group A. To verify this assumption, we performed a Pearson correlation test to determine if the preferred elicitation method is related to the perceived recommendation quality and recommendation accuracy. The results of the correlation between the recommendation quality variables and the preferred elicitation method variables showed that the two concepts are very strongly and significantly correlated *($|r| > .7$, $p < .001$)*. Correlating the recommendation accuracy variables with the preference elicitation concept variables also revealed that the two concepts are very strongly and significantly correlated *($|r| > .5$, $p < .001$)*. Finally, we performed regression analysis to determine which variables of the preferred elicitation method contributes to the perceived recommendation quality and accuracy. The output of the regression model suggests that the prefer_highlighting variable alone contributes (prefer_typing variable is excluded from the model) to both perceived recommendation quality and accuracy *[$R_2 = .526$, $F(1, 47) = 51.20$, $p < .001$]* and *[$R_2 = .375$, $F(1, 47) = 43.08$, $p < .001$]* respectively. The results obtained from the analyses confirms the assumption that the difference in the participants' preference for an elicitation method (highlights vs. Typing) between the two groups is as a result of their perceived recommendation quality and accuracy. That is, the participants in Group B's preference for typing search queries to guide as opposed to using highlights to guide recommendation is linked to the quality and accuracy of the recommendations they received.

H1.2: *The preference elicitation method has a positive effect on the user experience.*

This hypothesis assumes that the preference elicitation method influences the user experience. For example, if a user is dissatisfied (or otherwise) with the use of highlights to guide recommendation, it could affect his/her experience with, and evaluation of the recommender system. Knijnenburg et al., (2011) suggest that the user experience measurements should distinguish the evaluation objects of the recommender system: the process, outcome, and system itself. *Perceived effort to use system* is the process-related experience concept that assesses the effort and time required to operate the system; *perceived system effectiveness* is the system-related experience concept that measures the users' evaluation of the recommender system's effectiveness, and *recommendation choice satisfaction* is the outcome-related experience concept that measures the users' satisfaction with the chosen items read. To determine whether the user experience is influenced by the preference elicitation method, correlation and regression analysis were conducted to examine the relationship between the concepts that measure the user experience and the preference elicitation method. Pearson correlation test results reveal that the preference elicitation method concepts are significantly related to the user experience concepts $(|r| > .44, p < 0.003)$. More specifically, the variables measuring the user experience concepts are positively related to the prefer_highlights variable, and negatively correlated to the prefer_typing variable. The prefer_highlighting variable was observed to have contributed to two of the three concepts that measured the user experience (recommendation choice satisfaction and perceived system effectiveness) with coefficients $[R_2 = .542, F(1, 47) = 38.82, p = .001]$, and $[R_2 = .317, F(1, 47) = 15.05, p < .001]$ respectively; while the prefer_typing variable was excluded from the model. However, neither prefer_highlighting nor prefer_typing variables contributed to the effort to use system concept.

As earlier mentioned, the effort to use system concept assesses the system's process of generating recommendations, while recommendation choice satisfaction assesses the outcome – recommendations produced and perceived system effectiveness evaluates the system. Therefore, it is understandable that the elicitation method may not necessarily influence or affect the process by which the system generates recommendation, the process by which the system generated recommendations rather has to do with the underlying algorithms and structure of the recommender system. However, for the outcome-related concept, recommendation choice satisfaction, which is directly influenced by the elicitation method, and perceived system effectiveness concept, the regression analysis indicates that the prefer_highlighting variable has a significant positive regression weight. Therefore, we conclude that the use of highlights to guide recommendations had a positive effect on some aspects of the user experience.

TABLE 3
MEAN RESPONSES AND T-TEST RESULTS OF THE PERCEIVED RECOMMENDATION QUALITY AND ACCURACY VARIABLES

Variable	Group A Mean Responses	Group B Mean Responses	T-Values
Recommendation Quality			
like_articles	4.30	2.37	t(47) = 3.42 p = 0.001 d = 1.45
valuable_articles	4.45	2.46	t(47) = 3.55 p = 0.001 d = 1.47
too_many_irrelevant_articles	1.76	3.71	t(47) = -2.33 p < 0.001 d = 1.11
didn't_like_articles	1.40	3.38	t(47) = -1.91 p < 0.001 d = 1.48

Recommendation Accuracy			
well_chosen_articles	4.32	2.17	$t(47) = 3.12$ $p = 0.005$ $d = 1.62$
relevant_articles	4.44	2.33	$t(47) = 2.85$ $p < 0.001$ $d = 1.26$
high_rating_articles	4.14	2.50	$t(47) = 2.37$ $p < 0.001$ $d = 1.85$
appealing_articles	4.08	2.42	$t(47) = 2.00$ $p < 0.001$ $d = 1.71$

What Components of the Framework Affect the User Experience?

This research question examines the effects of the subjective system aspects, personal characteristics and situational characteristics of the evaluation framework on the user experience.

Subjective System Aspects on User Experience

The subjective aspects of the system provides an evaluation of the objective aspects (e.g. algorithm) as perceived by the users. It also provides explanations on the resulting user experience (Knijnenburg et al., 2011). For example, does a high perceived recommendation quality lead to enhanced user experience? To examine the effect, using the hypotheses below, we examine the relationship between the two concepts (subjective system aspect and user experience), compute independent t-tests on the two group conditions, and perform regression analysis to identify the predictors.

***H2.1:** There is significant difference in the perceived recommendation quality between the two group conditions.*

To determine whether participants of the two groups judge the recommendation quality differently, independent sample t-test is also performed on the four variables that were used to measure the participants' perceptions on the recommendation quality (perceived recommendation quality). This test is intended to assess the algorithm behind the recommendations used in the two group conditions are significantly different; where participants in Group A received recommendations based on their metacognitive activities and the LDI model, and participants in Group B received random recommendations. More specifically, the variables measuring the concept perceived recommendation quality focused on assessing if the articles generated for recommendation were appropriate and relevant to completing the task. Table 3 shows the mean responses to the variables measuring this concept for both groups. The results of the t-test shows that this difference is significant with a large effect size for the four variables measuring the concept: like_articles [$t(47) = 3.42$, $p = .001$, $d = 1.45$], valuable_articles [$t(47) = 3.55$, $p = .001$, $d = 1.47$], irrelevant_articles [$t(47) = -2.33$, $p < .001$, $d = 1.11$], and didn't_like_articles [$t(47) = -1.91$, $p < .001$, $d = 1.48$].

***H2.2:** There is significant difference in the perceived recommendation accuracy between the two group conditions.*

Similar to the hypothesis above, independent sample t-test is performed to further determine if the algorithm behind the recommendations used in the two group conditions are significantly different; where participants in Group A received recommendations based on their metacognitive activeness and the LDI model, and participants in Group B received random recommendations. The variables measuring the perceived recommendation accuracy concept measure the participants' ratings of the recommendation they received. The results of the t-test and the mean responses on the participants' perception on the recommendation accuracy is also shown in Table 3. The t-test result reveals that the difference in the perceived recommendation accuracy between the two group conditions is significant with a large effect size for the four variables measuring the concept: well_chosen_articles $[t(47) = 3.32, p = .005, d = 1.62]$, relevant_articles $[t(47) = 2.85, p < .001, d = 1.62]$, high_rating_articles $[t(47) = 2.37, p<.001, d = 1.85]$, and appealing_ articles $[t(47) = 2.00, p < .001, d = 1.71]$. To determine whether the participants' perception of the recommender system's quality is related to the perceived recommendation accuracy, correlation and multiple regression analyses were performed on the variables measuring the two concepts. The results of the correlation test shows that both concepts are very strongly and significantly correlated with correlation coefficients of $(|r| > .6 \text{ and } p < .001)$, while the regression model produces $[R_2 = .82, F(1, 47) = 58.43, p < .001]$, and excluded irrelevant_articles and didn't_like_articles variables from being predictors.

H2.3: *The users' subjective system analysis of the recommender system affects the user experience.*

Having established that there is a significant difference in the perceived recommendation quality, accuracy and preferred elicitation method (subjective system aspects) between the two group conditions, this hypothesis investigates how the perceptions result in specific user experience (recommendation choice satisfaction, recommender system effectiveness, perceived effort to use system). For example, whether a higher perceived recommendation quality leads to a higher satisfaction with the recommendations. Computing independent t-test on the concepts of the subjective system aspects and the user experience reveals that for the four variables that measure the recommendation choice satisfaction concept: enjoyed_reading_articles, task_appropriate_articles, and articles_fit_preference, articles_waste_of_time, there is a significant difference between the two groups; where the t-values for the variables are $[t(47) = 4.37, p < .001, d = 2.39]$, $[t(47) = 3.01, p < .001, d = 2.66]$, $[t(47) = 2.40, p = .003, d = 1.85]$, $[t(47) = -4.21, p < .001, d = 2.21]$ respectively. The analysis also revealed that two of the four variables that measure the recommender system effectiveness are significantly different better_articles_with_system $[t(47) = 4.62, p < .001, d = 2.43]$, better_articles_without_system $[t(47) = -2.36, p = .004, d = 1.71]$ between the groups; and for one variable (invest_lot_of_effort) of the perceived effort to use system concept showed a significant difference between the two groups with t-values $[t(47) = 2.85, p < .001, d = 1.54]$. The variables of the recommender system effectiveness that weren't significantly different between the two groups are recommend_system, and sys_aware_highlights. This suggests that participants in both groups may have been satisfied with these aspects of the system despite the variation in the method behind the recommendations generated. The results further support the notion that the use of highlights, may be suitable to guide recommendation, and also facilitates metacognition. Similarly, the two variables (system_easy_to_use and recs_take_too_much_time) of the perceived effort to use system concept that weren't significantly different between the two groups reveals that the system is easy to use (where the mean responses from both groups are greater than *4.3*), and it doesn't take too long to provide recommendation (the mean responses from both groups are less than *2.0*).

In general, the results obtained from the correlation tests reveal that there is a strong and significant relationship between the variables representing the user experience concepts and the participants' perceived recommendation quality and accuracy, with correlation coefficients $(|r| > .50, p < 0.005)$. The variables system_easy_to_use and recs_take_too _much_time are positively related to perceived recommendation quality and perceived recommendation accuracy concepts, while the invest_lot_of_effort variable is negatively related. Three of the four perceived system effectiveness variables recommend_system, sys_aware_highlights, and better_articles_with_system are also positively related to the perceived recommendation quality and perceived recommendation accuracy concepts while the variable better_articles_without_system is negatively related. A similar relationship is observed for the perceived choice satisfaction variables; where variables enjoyed_reading_articles, task_appropriate_ articles, and articles_fit_preference are positively related, and the variable articles_waste _of_time is negatively related to the perceived recommendation quality and perceived recommendation accuracy concepts.

The result of the regression model reveals that only two of the four variables that measure perceived recommendation quality influence the recommender system effectiveness and recommendation choice satisfaction concepts of the user experience. The variables/predictors like_articles and valuable_articles produced *[$R_2 = .46, F(1, 47) = 64.39, p < .001$]* for recommender system effectiveness, and *[$R_2 = .77, F(1, 47) = 53.18, p < .001$]* for recommendation choice satisfaction concepts. All the variables that measure perceived recommendation accuracy were observed to be predictors of the regression model for the recommender system effectiveness concept which generated *[$R_2 = .21, F(1, 47) = 18.25, p < .001$]*, and *[$R_2 = .73, F(1, 47) = 82.91, p < .001$]* for recommendation choice satisfaction. However, none of the variables measuring perceived recommendation quality and accuracy was discovered to influence the effort to use system concept. Therefore, based on the results of the analyses performed, we accept the hypothesis that the subjective system aspects positively affect some of the concepts that measure user experience. More specifically, for the three subjective system aspects the following was discovered: (a) prefer_highlights variable of the preference elicitation method influenced the recommender system effectiveness and recommendation choice satisfaction concepts, but did not influence the effort to use system concept (b) like_articles and valuable_articles of the perceived recommendation quality also influenced the recommender system effectiveness and recommendation choice satisfaction concepts, but did not influence the effort to use system concept (c) all the four variables of the perceived recommendation accuracy concepts influenced the recommender system effectiveness and recommendation choice satisfaction concepts, but also did not influence the effort to use system concept. This implies that none of the subjective system aspects contributed to the user's perceived effort to use the system.

Personal Characteristics on the User Perception and User Experience

This research questions examines if some of the personal characteristics of the users affect their perception of the quality, accuracy of the recommender system and/or the user experience. As popularly mentioned in literature, the personal characteristics of users that influence perception and user experience are gender and domain knowledge. These personal characteristics were obtained from the pre-experiment (demographics) questionnaire administered to the participants. From the data analyzed, a total 22 males and 27 females participated in the user study experiment. The questionnaire item used to collect information about the domain knowledge of the participants had three response categories, represented as: novice, intermediate, and expert. *91.8%* of the participants indicated to be not familiar (novice) with the domain (source reading text), while for the intermediate and expert levels, *4.1%* of the participants indicated to belong to each of the categories. Given that the data obtained for each of the domain knowledge categories wasn't significantly sufficient, we are not able to assess the effects of the domain knowledge on the participants' perceptions of the recommendation quality, accuracy and user experience. Independent t-tests were performed to measure whether there is a significant difference between the perception of males and females on the recommendation quality, accuracy and user experience. The results obtained from this data analysis revealed that there is no significant difference between the perception and user experience of the males and females that took part in the user study. Therefore, to answer the research question, we conclude that the personal characteristics of the participants had no effect on user experience nor perceptions; where the gender variable revealed no effects, and *91.8%* of the participants were novices to the domain of the educational task to be completed.

Situational Characteristics on the User Perception and User Experience

Similar to the analysis performed on the participants' personal characteristics, this research questions examines if some of the situational characteristics of the users have an effect on their perception of the quality, accuracy of the recommender system and/or the user experience. The situational characteristics of users that have been widely noted to influence the perception and user experience are trust in technology and privacy concerns. The situational characteristics of the participants were obtained from the post-experiment (feedback) questionnaire administered. *71.6%* of the participants reported to have general trust in technology and do not have privacy concerns with the system, while *28.4%* reported not to have trust in technology and had privacy concerns with the system. Computing independent t-tests on the two groups of users (those who trust in technology and those who don't) reveals that there is no significant difference in the user experience and perception between the group of users. Also, there is no significant difference in the user experience between the users who have privacy concerns with the system and those who don't. Therefore, we can conclude that the situational characteristics of the participants had no effect in the perception of the recommendation quality and accuracy assessments, and the user experience.

Relationship Between the User Experience Concepts

To determine how the three concepts that measure the user experience relate and contribute to each other, correlation and regression analysis were performed. For simplicity, three composite variables were created for each concept and used for the analysis and the results of the analyses revealed that: (a) in the regression model for recommendation_choice_satisfaction, only recommender_system_effectiveness is a predictor (effort_to_use_system is excluded) and produced $[R_2 = .461, F(1, 47) = 18.366, p < .001]$. Furthermore, the correlation test also showed a positive and significant correlation between the concepts having coefficients of $(|r| > 0.65, p < .001)$. (b) effort_to_use_system concepts is a predictor to the recommender_system_effectiveness concept, which produced $[R_2 = .314, F(1, 47) = 6.972, p < .001]$, and the correlation test also showed a positive and significant correlation between the concepts having coefficients of $(|r| > 0.64, p < .001)$.

In sum, this section investigated the effects and influence of three components (subjective system aspects, personal characteristics, and situational characteristics) of the user-centric framework deployed to evaluate the recommender system on the user experience of the participants that participated in the user study experiments. The data analysis also examined whether the personal and situational characteristics of the users also affects their perception of the recommendations (as an indirect link to the user experience), it was discovered that the perception influences the user experience. The results of the data analysis performed showed that only the subjective system aspects component contributed to the user experience.

What Components of the Framework Affects the User Interaction?

Similar to the data analysis conducted in in the previous section, this research question seeks to examine the effect(s) of the preference elicitation methods, user experience, personal characteristics, and situational characteristics on the user interaction. Two variables are used to measure the concept of user interaction: number of recommended articles clicked, and number of highlights created; where the number of recommended articles clicked variable is computed for each participant and represents the sum of all the articles clicked on among the recommended articles they received, and number of highlights created variable also computed for each participant is the sum of all the highlights-tags created on all the articles clicked on, from among the list of recommendations received. Information about the user interaction is obtained from the logged data for each participant. The effect of each component on the user interaction is discussed in the subsections below.

Effects of the User Experience on User Interaction

Here, we hypothesize that given the two group conditions provide recommendations using different approaches, the difference in the methodology should be reflective in users' engagement with the recommendations provided. That is, since the participants in Group B receive random recommendations, there may be fewer relevant and task-appropriate articles to read and make highlights from, thus the number of clicks and articles operated on might be fewer compared to Group A participants who receive recommendations that are tailored to the highlights created. To determine whether the perception of the users has any effect on the user interaction, the hypotheses below investigate the effects and relationships of a number of concepts and variables on the user interaction.

H3.1: *There is significant difference in the user interaction between the two group conditions.*

The results of the descriptive statistics analysis of the user interaction variables revealed that Group A participants had an average of *8.86* number of recommended articles clicked, and *33.32* number of highlights created, while Group B participants had an average of *3.74* number of recommended articles clicked, and *12.38* number of highlights created. Using t-test analysis, we further examined whether there is a significant difference between the user interaction variables between the two group conditions. The results of the analysis confirms the hypothesis that there is a significant difference between the user interaction of the two groups; where number of recommended articles clicked: *[$t(47) = 5.47$, $p = 0.01$, $d = 3.23$]* and number of highlights created: *[$t(47) = 4.91$, $p = 0.04$, $d = 2.61$]*. Table 4 shows the details of the analysis.

TABLE 4
MEAN RESPONSES, T-TEST RESULTS OF THE USER INTERACTION VARIABLES

Variable	Group A Mean Responses	Group B Mean Responses	T-Values
rec_articles_clicked	8.86	3.74	t(47) = 5.47 p = 0.01 d = 3.23
highlights_created	34.76	11.52	t(47) = 4.91 p = 0.04 d = 2.61

H3.2: *The user experience concepts affect the user interaction.*

Correlation test and regression analysis are performed to determine the relationship between the concepts as well as to identify which of the three concepts that measure the user experience contributed to the user interaction variables. The results of the correlation test suggests that the user experience concepts are positively and significantly related to the user interaction, while the results of the regression analysis indicates that at least one variable each, of the three concepts that measure the user experience are predictors in the user interaction. The variables are: task_appropriate_articles of the recommendation choice satisfaction concept which produced *[$R_2 = .573$, $F(1, 47) = 65.08$, $p < .001$]*, better_articles_with_system of the recommender system effectiveness concept produced *[$R_2 = .527$, $F(1, 47) = 52.29$, $p < .001$]*, and invest_lot_of_effort of the effort to use the system concept produced *[$R_2 = .198$, $F(1, 47) = 5.12$, $p = .003$]*. To measure the effect of each concept as a unit, composite variables were created for each of the user experience concepts. Computing regression analysis on the composite variables to examine the effects on the user interaction gave the following results: recommendation choice satisfaction: *[$R_2 = .434$, $F(1, 47) = 36.02$, $p < .001$]*, recommender system effectiveness: *[$R_2 = .275$, $F(1, 47) = 27.29$, $p < .001$]*, and effort to use system: *[$R_2 = .098$, $F(1, 47) = 4.48$, $p < .001$]*. Based on these results, we accept the hypothesis that the user experience influences the user interaction. The variable that contributes the most to the user interaction is the task_appropriate_articles of the recommendation choice satisfaction concept, which hints that make more metacognitive interactions when provided with appropriate learning materials.

Effects of Personal, Situational Characteristics on User Interaction

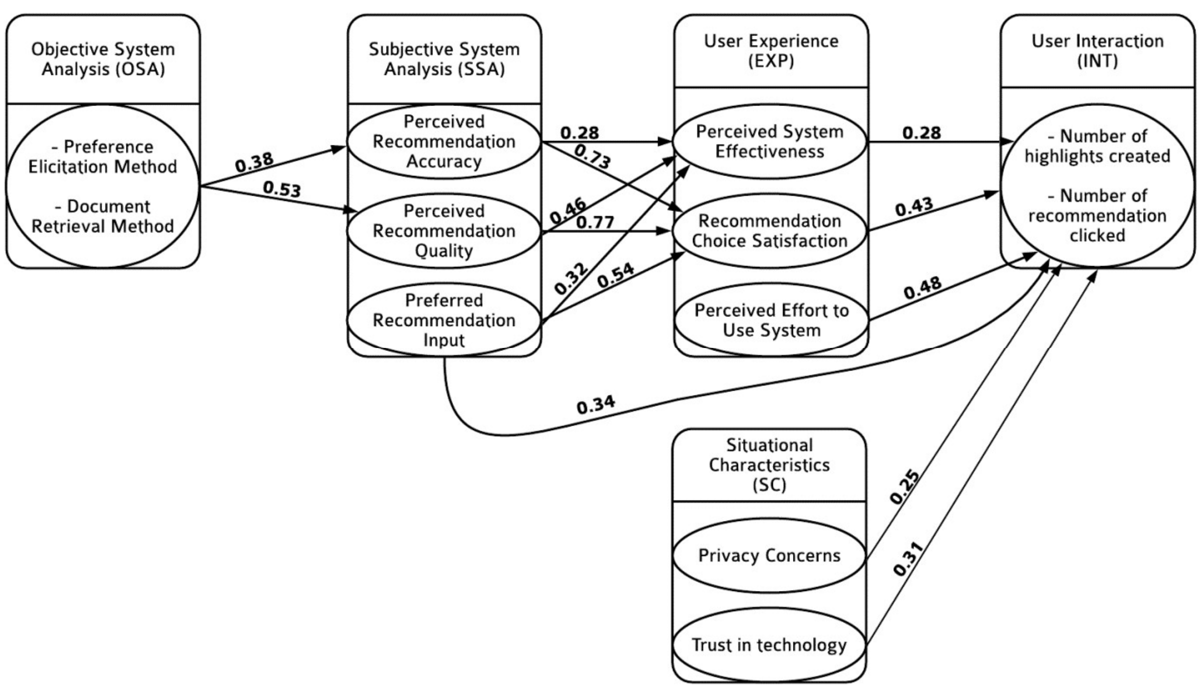
As aforementioned, the only personal characteristics variable we have sufficient data for analysis is gender: M/F. To determine if there is significant difference between the gender variable and the user interaction, an independent t-test was performed. The result of the test showed that there is no significant difference between the user interaction of the males and females that took part in the experiment.

Independent t-tests and regression analysis are performed to investigate the effects of the situational characteristics (trust in technology and privacy concerns) on the user interaction variables. The results reveal that (a) there is a significant difference between the interaction of users who trust in technology and those who don't. This is also true for users who had privacy concerns with the system and those who didn't, which produced t-values *[t(47) = 6.32, p < 0.001, d = 2.89]* and *[t(47) = 5.01, p < 0.001, d = 2.77]* respectively. The regression analysis generated trust in technology: *[R_2 = .314, F(1, 47) = 16.18, p < .001]*, privacy concerns: *[R_2 = .248, F(1, 47) = 10.33, p < .001]*. These results show that the situational characteristics of the users affect the user interaction, where the lack of trust in technology and having privacy concerns about the system disclosing personal information influenced the user interactions, and otherwise.

Effect of Preference Elicitation Method on User Interaction

Similar to the user experience, we hypothesize that the preference elicitation method also has a positive effect on the user interaction, where the user interaction refers to the participant's engagement with the recommendations. Since there are two types of highlights involved in the user experiments; where the first set of highlights are created to guide recommendations and the second set of highlights made on the list of recommendations to complete the educational task, the user interaction concept strictly considers the highlights created to complete the educational task (num_highlights_created) as well as the number of recommendations clicked (num_recs_clicked). Computing correlation and regression analysis shows that the user interaction concept is significantly related to preference elicitation method; where prefer_highlighting variable is positively correlated having coefficients *(|r| > .61, p < .001)*, and prefer_typing is negatively correlated *(|r| > -.40, p < .004)*. The regression model obtained further revealed that only the prefer_highlighting variable is a predictor (prefer_typing is removed). This indicates that the prefer_highlighting variable contributes to the user interactions *[R_2 = .339, F(1, 47) = 24.06, p < .001]*. Therefore, we conclude that the user interaction was affected or influenced by the use of highlights.

FIGURE 3
GRAPHICAL REPRESENTATION OF THE RELATIONSHIPS BETWEEN THE CONCEPTS, VARIABLES EVALUATED OF THE RECOMMENDER SYSTEM



Based on the user-centric framework by Knijnenburg et al., (2012) we adopted to evaluate the recommender system developed, Figure 3 reveals the relationships between the six concepts that play a role in the user experience of recommender system, which is based on the results obtained from the regression analyses performed to determine how the variables in the concepts affect each other. We observed the following (a) Relationship between OSA and SSA: The recommender system's methodology contributes to the perceived recommendation accuracy and quality by *38%* and *53%* respectively, (b) Relationship between SSA and EXP: The SSA variables (perceived recommendation accuracy, perceived recommendation quality and preferred recommendation input) contribute to the user experience, (c) Relationship between EXP and INT: Each of the three user experience variables investigated contributed to the user interaction, where perceived system effectiveness accounted for *28%*, recommendation choice satisfaction *43%* and perceived effort to use the system *48%*, (d) Relationship between INT and SC: The variables of SC (privacy concern and trust in technology) were observed to contribute to the user interactions by *25%* and *31%* respectively.

CONCLUSION AND FUTURE WORK

A personalized learning recommender system was designed to support self-regulated learning. A recommender system in the context of learning can be considered as a useful tool for finding relevant documents among the vast amount of materials available on the Internet, as well as alleviating information overload which has been identified as one of the main problems learners encounter in online learning and when searching for the "right" information to satisfy their needs. The development of personalized learning recommender systems includes a learner model which is used to obtain/infer information about the learner, such as the learning goal, learning style, prior knowledge, and the information collected is used to guide recommendation. we investigated the possibility of using highlights, one of the many metacognitive reading activity a learner engages in while reading to achieve personalization. Specifically, the metacognitive activity used in this study is highlights, and the metacognitive aspects of creating highlights lies in the act of the learner judging whether to mark and what to mark. For the retrieval of relevant documents, the Latent Dirichlet Index (LDI) model is used. The LDI method leverages probabilistic topic modelling approaches for representing documents in a topic space where the topics can be seen as index terms. Together with the metacognitive activities, the recommender system provides recommendations that are related to the learners' information seeking needs.

To evaluate the system developed, a user-centric framework for evaluation model was adopted. Three main research questions and a number of hypothesis were tested and analyzed using the information collected from the user study via two sets of questionnaires administered to participants during the experiments. The results of the first research question which examined the user's perception on the use of the highlights as an appropriate preference elicitation method to guide recommendations revealed that that the use of highlights is considered suitable to guide recommendation, and also facilitates metacognition. The second research question examined the components of the framework that influenced the user experience. Results from the data analysis suggests that three components in some way affect the user experience they are: the subjective system aspects, personal characteristics and situational characteristics. The third research question also investigated the components that affected the user interaction. Three components were identified to contribute to the user interaction concepts they are: user experience, situational characteristics, and preference elicitation method.

The design, implementation, analysis, and evaluation of our personalized learning recommender system to support self-regulated learning provides a first step of what needs to be examined as the basis for investigating the effects on learners' achievements when they use the recommender system. While the system works, as judged by the users, investigating what and how much learners using the system actually benefit by using it is an important next step for potential future work. Future research can done to investigate how the integration of other TEL functionalities might be included in a personalized learning recommendation system. Some of the TEL functionalities that could be included to enhance learning are: collaborative learning settings, and a question generation module. According to Sansivero (2016), collaborative or active learning is a methodology that transforms that traditional lecture or teacher focused classroom into a student or learning centred room. In a collaborative learning setting, the students work together to help each other understand a content, solve problems or create projects and products with the instructor working as a moderator or facilitator. Furthermore, it encourages trust building, communication, practical learning/application, and acceptance and enhances problem-solving skills, therefore could be a potentially valuable add-on feature for the system.

Assessment through posing questions is considered an integral part of learning. It can be leveraged to gather data that would be helpful to better understand the strengths and weaknesses of students' learning (Harris and Hodges, 1995). As a reflective process in which learners evaluate their performance and determine how to improve, an automatic question module could make available, important data that can be used to measure the progress of learning with respect to the learning goals and objectives. Research has also shown that learners need assessments to learn, regardless of whether they are posed by teachers or formulated by the students themselves, and also that assessments increase comprehension for learners (Rittle-Johnson, 2006). Therefore, the inclusion of an assessment module could be beneficial.

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