Modeling and predicting information search behavior

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ABSTRACT
This paper looks at two limitations of cognitive models of web-navigation: first, they do not account for the entire process of information search and second, they do not account for the differences in search behavior caused by aging. To address these limitations, data from an experiment in which two types of information search tasks (simple and difficult), presented to both young and old participants was used. We found that in general difficult tasks demand significantly more time, significantly more clicks, significantly more reformulations and are answered significantly less accurately than simple tasks. Older persons inspect the search engine result pages significantly longer, produce significantly fewer reformulations with difficult tasks than younger persons, and are significantly more accurate than younger persons with simple tasks. We next used a cognitive model of web-navigation called CoLiDeS to predict which search engine result a user would choose to click. Old participants were found to click more often only on search engine results with high semantic similarity with the query. Search engine results generated by old participants were of higher semantic similarity value (computed w.r.t the query) than those generated by young participants only in the second cycle. Match between model-predicted clicks and actual user clicks was found to be significantly higher for difficult tasks compared to simple tasks. Potential improvements in enhancing the modeling and its applications are discussed.

Categories and Subject Descriptors
H.3.3 [**Information Search and Retrieval**]: Search Process, Selection Process.

H.5.1 [**Information Interfaces and Presentation**]: Hypertext navigation.

General Terms
Performance, Design, Experimentation, Human Factors

Keywords
Modeling, Information Search, Cognitive Factors, Aging

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1. INTRODUCTION
The total number of indexed websites on the internet has crossed the four billion mark according to a recent statistics[1]. Navigating through such abundance of information remains still a challenge for many. Therefore, several search engines have been built that filter and present only that information which is most relevant to the user's goal. A typical process to search information on the internet proceeds as follows: the user opens a search engine URL such as http://google.com with a question or a goal in mind. Based on his understanding of the goal and his/her prior knowledge, the user formulates a search query. Search engine retrieves the top-10 (and more) most relevant documents and presents them to the user (commonly called search engine result pages or SERPs, henceforth). The user evaluates one or more of these results shown by the search engine. At this stage, the user can take two actions: either click on one of the search engine results or reformulate the search query to get a fresh set of SERPs. If the user does the latter, the process repeats. But if s/he does the former, i.e., if the user clicks on any one of the search engine results, then a website corresponding to that result is opened. At this stage again, user has two choices: either come back to the SERPs or click on more hyperlinks within the opened website and evaluate its content more deeply. This process goes on until either the user finds the information s/he was looking for or is frustrated and leaves. We can clearly see that several cognitive processes are involved in the process of interacting with the internet: memory, attention, problem solving, reasoning, comprehension and decision making (refer also the model by Sharit et al. [31]). Several cognitive factors such as age, domain knowledge, internet experience, etc. in turn influence either positively or negatively the above cognitive processes. One can also see distinctly two major paradigms in the above process: search by query or simply searching, which involves interaction mainly with the search engines and search by navigation or browsing which involves interaction mainly with the websites opened from the search engine results [27].

[1] http://www.worldwidewebsize.com/ accessed on 5th Feb 2015.

Many attempts to model the cognitive processes involved in web-navigation have been made. Most of them are inspired by Information Foraging Theory introduced by Pirolli and Card [29], which states that, when browsing on the web, people take only those actions (such as clicking on a hyperlink) that maximizes their information gain in relation to the cost of taking that action. The theory also introduces the concept of *information scent* which is the (imperfect) estimate of the value or cost of information sources represented by proximal cues (such as hyperlinks and icons). These cognitive models of web-navigation have two main limitations:

- They do not account for the entire process of information search: i.e., all the models developed so far have focused primarily on search by navigation or navigation within websites and have ignored search by query or interaction with a search engine in spite of the fact that most information search processes start with the search engine.

- They do not fully characterize all the factors that influence the cognitive processes involved in web-navigation. Of all such factors, we focus on age in this paper for various reasons. The percentage of population aged over 65 years is increasing and continues to grow, especially in OECD countries. Also the percentage of those aged over 65 years who use the internet is rapidly increasing. Though internet has grown tremendously and almost invaded every aspect of our lives, several barriers still exist for old people to really make it an irreplaceable part of their daily lives as it normally is for young people [32]. Aging leads to a rapid decline in fluid intelligence (processing speed, cognitive flexibility or ability to switch processing strategies, attentional control and visuospatial span) as well as in motor skills [17, 18, 34]. Some of these abilities are directly linked to the skills required to process information from the internet. In spite of several cognitive problems that they face, old people are now increasingly using the internet to do many daily activities such as reading or watching news, banking, reading health related information, contacting friends over email, talking to their grandchildren, etc. They now form one of the fastest growing users of the internet [1, 11].

In this paper, we try to address the above two limitations of cognitive models. Section 2 reviews briefly some of the cognitive models developed so far. Section 3 provides a snapshot of some of the research works that studied the influence of aging on information search process and lists the main research questions we are interested in. Section 4 gives details of the experiment we carried out. Section 5 describes how cognitive models of web-navigation can be used to predict user interactions with a search engine. We discuss our major findings and conclude in Section 6. Possible ideas for extending our work are provided in Section 7.

2. COGNITIVE MODELS OF WEB-NAVIGATION

2.1 Method for Evaluating Site Architectures

Method for Evaluating Site Architectures (MESA) developed by Miller and Remington [25] focuses on the relationship between information architecture of a website and navigation patterns of users. By varying the link quality and using links that are not fully descriptive of the target goals, user behavior is modeled. The situation when the user is not sure of his/her goal or is not knowledgeable enough to assess the relevance of the link texts to the goals is modeled. It uses three main cognitive principles: *limit capacity principle*, that is, the model performs only those actions that are in the physical and cognitive range of a normal human, *simplicity principle*, that is, the model favors simple approximations to complex features that add little value, for example though it is known that different users take different amount of time to evaluate hyperlinks, the model assumes a fixed time based on a reasonable estimation from large data and *rationality principle*, that is, the model assumes that users are rational and they always choose the best strategy. The model however does not give an account of how the link relevancies are assessed, but focuses on the effectiveness of selecting various links given their relevance to the search goal. Also the model assumes that the structure of the website is known beforehand. This model is focused entirely on navigation within a website and does not account for the interactions with a search engine.

2.2 CoLiDeS

CoLiDeS or Comprehension-based Linked Model of Deliberate Search developed by Kitajima et al. [22] divides user navigation behavior into four stages of cognitive processing: parsing the webpage into high-level schematic regions, focusing on one of those schematic regions, elaboration/comprehension of the screen objects (e.g. hypertext links) within that region, and evaluating and selecting the most appropriate screen object (e.g. hypertext link) in that region. CoLiDeS is based on Information Foraging Theory and connects to the Construction-Integration reading Model of Kintsch [21]. In CoLiDeS information scent is operationalized as the semantic similarity between the user goal and each of the hyperlinks. Based on the semantic similarity values, the model predicts that the user is most likely to click on that hyperlink which has the highest semantic similarity value. This process is repeated for every new page until the user reaches the target page. CoLiDeS uses Latent Semantic Analysis (LSA) introduced by Landauer et al. [23], to compute semantic similarities. It has been successful in simulating and predicting user link selections, though the websites and web pages used were very restricted. The model has also been successfully applied in finding usability problems, by predicting links that would be unclear to users [2, 3]. Two extensions were made to the original CoLiDeS later by using information from already clicked hyperlinks to predict and model backtracking behavior [19] and by using semantic information from pictures to improve the accuracy of predictions [33, 20]. All three models CoLiDeS, CoLiDeS+ and CoLiDeS + Pic are focused only on navigation within a website and do not account for interactions with a search engine.

2.2 SNIF-ACT

SNIF-ACT (Scent-based Navigation and Information Foraging in ACT Architecture) was developed by Pirolli and Fu to predict navigational choices and simulate user behavior as they perform unfamiliar information retrieval tasks on the web [30]. Decisions such as which hyperlink to click, where to go next, when to leave the website are made based on the measure of information scent. SNIF-ACT 1.0 assumed that users assess all the hyperlinks on a web-page before making a choice. However, several studies showed that the user choices are sensitive to the location of the hyperlinks on a web-page. SNIF-ACT 2.0 was later introduced by Fu and Pirolli [15] incorporating mechanisms from Bayesian Satisficing Model [14]. It combines the measure of information scent, the position of hyperlinks on a search result page and the number of hyperlinks evaluated so far into a satisficing process that determines whether to continue to evaluate more hyperlinks

or to click on the best hyperlink found so far. The authors showed that SNIF-ACT 1.0 better predicts user choices compared to a model which assigns rank purely based on its position on a web-page. Experimental data used to test SNIF-ACT 1.0 used primarily navigation data and did not make a clear distinction between interaction with a search engine and navigation within a website. Also, the improved version of SNIF-ACT 2.0 which takes into account the position as well as the information scent of a hyperlink was empirically tested only on data consisting of navigation within a website and not on data consisting of interaction with a search engine.

In summary, the cognitive models described above model the user navigation behavior with websites and do not account for the interactions with a search engine. In the next section, we look at some of the experimental literature on the influence of age on information search performance.

3. EFFECT OF AGING ON WEB-NAVIGATION BEHAVIOR

It was long believed that old people consider using the internet complicated and difficult to learn and that they do not perceive any benefit from it [13, 24]. This is no longer the case: recent studies show that old are now as enthusiastic as young in using the web [35]. Barriers do exist due to the natural decline in motor skills and their fluid intelligence involving processing speed, cognitive flexibility or ability to switch processing strategies, attentional control and visuospatial span [17, 18, 34]. Because of this, old people are known to be slow and less efficient when using the internet. They click on less number of pages, take longer to click, make unnecessary repeated visits to already visited pages, etc. [5, 6, 7, 16, 28].

However crystallized intelligence increases and/or becomes stable with aging. Crystallized intelligence involves prior knowledge, experience and vocabulary skills. Therefore it is higher for old people compared to young [17, 18, 34]. So the question is can the higher crystallized intelligence of old people help them in using the internet as well as the young people? If yes, under what conditions? Pak and Price [28] studied if differences in information architecture of a website could reduce age-related differences in performance. They used two kinds of architectures, one was hierarchically organized and the relationship between the menu and the page was one-to-one, the other was tag-based and the relationship between the menu and the page was many-to-one. As expected, they found that old people performed better on tag-based interface which had greater demand on vocabulary and less on spatial abilities. However, the material used in their study did not have any search engine results.

Some recent research works have studied if higher crystallized intelligence of older people could be of advantage when performing complex and more difficult information search tasks? Results from Dommes et al. [12] say that old people use fewer keywords, overall fewer queries, open fewer websites per question than young people when the task is difficult. No such difference was found for total time taken to finish a task, time spent evaluating search results and accuracy of task-completion. That is, old people were performing differently than young people on difficult tasks on some performance parameters and not on the others. Sharit et al. [31] used a combined measure of performance that includes task-completion time, accuracy and difficulty of a task and found that young people achieved a significantly higher score on this combined measure than old people on complex tasks. However, a deeper analysis by the same authors between knowledge levels, internet experience, other cognitive abilities and performance revealed that knowledge alone was not sufficient to explain the differences in performance between young people and old people. As the task became more complex, performance became more dependent on a combination of knowledge and other abilities such as reasoning, working memory and perceptual speed. Contrary to the results from the two studies mentioned above, Chin et al. [6] found that old people performed better than young people on ill-defined tasks. This was explained with different strategies that young people and old people employed: old people used a top-down knowledge driven strategy which was more suitable for ill-defined tasks whereas young people followed a bottom-up interface driven strategy which was better suited for well-defined tasks. The material used in this study consisted of a website and did not involve any interaction with a search engine or SERPs. A later study by [8] used word search puzzle paradigm to examine the age differences in the underlying search mechanism showing that older adults did less exploration because they monitored the change of information gain differently than younger adults.

In summary, we find very few studies that use interaction with search engine as a context. Those few studies that do are inconclusive about the advantage that old people would have because of their higher crystallized intelligence in solving difficult tasks. We found only one study that suggests that providing link recommendations to help old people in utilizing their superior crystallized knowledge is useful [9]. However, the study is in the context of navigation within a website and not a search engine. Also, none of the cognitive models discussed in the above section take into account any of the age-related changes in their modeling. We address the above two limitations in this paper. The research questions of our study were: 1) What impact does aging and task difficulty have on information search performance, particularly when interacting with a search engine? We hypothesize that old people would be less efficient than young people, especially when solving difficult tasks. That is, they would take longer, click more, reformulate less and be less accurate than young people. 2) Can cognitive models of web-navigation developed so far be used to model and predict user interactions with search engines? We hypothesize that, just as information scent is the main driver of navigation within a website, it would also be the main driver of user decisions such as which search result on a SERP to click, when interacting with a search engine. Therefore, it would be very much possible to use cognitive models of web-navigation to model and predict user interactions with search engines.

4. EXPERIMENT

In order to study the first research question, we used data from the completed experiment on young and old participants interacting with a search engine conducted by [10].

4.1 Method

4.1.1 Participants

19 young participants ranging from 19 to 24 years (M = 22.7, SD = 1.8), and 20 old participants ranging from 64 to 73 years (M = 67.5, SD = 2.9) participated in the completed study.

4.1.2 Design

The experiment had three types of information search tasks: simple, difficult and open. For simplicity, we combined difficult

and open into one category as difficult. For simple tasks, participants could use words from within the task description as queries and in most cases, they could find the answer easily either in the blurbs of the search engine results or in one of the websites referred to by the search engine results. For difficult tasks, users had to frame queries using their knowledge and understanding of the task, the answer was not easily found in the blurbs of search engine results and often they had to evaluate information from multiple websites. A mixed factorial design was employed with task difficulty as a within-subjects factor and age as a between-subjects factor.

4.1.3 Material

The study had twelve information search tasks, six each from the domains of health and manga (a Japanese comic). Out of the six in each domain, three were simple and three were difficult. We focused only on health domain in this paper because this was more suitable for modeling purposes (explained in Section 5). The tasks were all presented in French. We provide the English equivalents of the tasks from health domain in Table 1.

Table 1. Information Search Tasks (English equivalents)

Simple
1. Which body parts can be affected by arthritis?
2. What medical term is used to refer to the partial death of a portion of heart muscle?
3. What is the name of the disease that causes pulmonary embolism?
Difficult
4. What causes the red color of blood?
5. Madame Martin, aged 60 years, suffers from chest pain and has trouble breathing. In your opinion, what disease could she be suffering from?
6. Alexandre, aged 7 years, often falls off his feet. He also has hearing problems. In your opinion, what disease could he be suffering from?

4.1.4 Measures

We measured the performance of participants in terms of the following dependent variables:

Task-completion time is computed from the moment of opening a browser and typing in the first query to the moment of answering the question. We also divided this overall time spent into the time spent only on SERPs and the time spent only on websites. The time spent only on SERPs includes the time taken to form keywords, reformulate queries etc.

Number of clicks is the total number of clicks made by a participant for each question. This is divided further into the number of clicks made only on SERPs and the number of clicks made only on websites.

Accuracy is measured as 0/1 depending on whether the participant could answer the task successfully (in which case the score is 1) or not (in which case the score is 0).

Number of reformulations is the total number of unique queries that a user could come up with for each task in the process of answering it (e.g., if participant added, deleted keywords or created new ones, we counted them as reformulations of query).

4.1.5 Procedure

Participants first did a demographic questionnaire. They were next presented with a domain knowledge test on the two topics health and manga. We found young participants had better knowledge of manga than old and old participants had better knowledge of health than young. Participants were presented with information search tasks from both domains in a counter balanced order. Participants were allowed to use only Google's search engine. At the end of every task, participants were instructed to go back to the main search engine page (http://www.google.fr). All queries generated by the users, URLs opened by them were logged in the backend.

4.2 Results

Only those participants were included in the analysis for which we had data of all six information search tasks. We had to drop data of 11 young and 11 old participants because we lost data of some tasks of these participants for technical reasons. We were finally left with eight young and nine old participants.

4.2.1 Task-completion time

Repeated measures ANOVA with age as between-subjects variable, task difficulty as within-subjects variable and mean task-completion time as dependent variable was conducted. Main effect of task difficulty was significant $F(1,15) = 32.47$, $p<.001$. Difficult tasks took significantly longer time than simple tasks. Main effect of age was not significant ($p>.05$). Interaction of age and task difficulty was not significant ($p>.05$). Figure 1 shows the means.

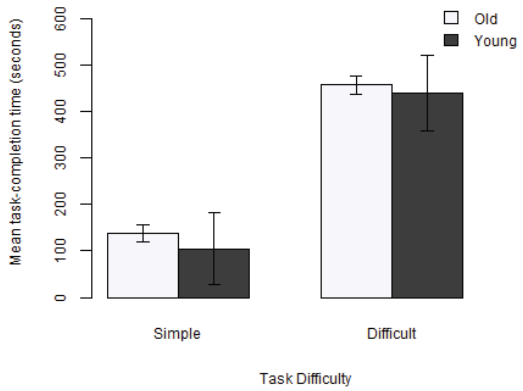

Figure 1. Mean (and standard errors) of task-completion time in relation to age and task difficulty

To investigate deeper if aging or task difficulty had any influence on the amount of time spent on SERPs or the time spent on websites, we next looked at the time spent on these two parts of search process separately. The time spent on SERPs or websites for difficult tasks was significantly higher than for simple tasks ($F(1,15) = 34.76$, $p<.001$, for SERPs and $F(1,15) = 13.2$, $p<.005$, for websites respectively). For both simple and difficult tasks, old participants spent significantly more time on SERPs than young participants (($F(1,15) = 4.5$, $p<.05$). There was no such difference for time spent on websites.

4.2.2 Number of clicks

Repeated measures ANOVA with age as between-subjects variable, task difficulty as within-subjects variable and mean number of clicks as dependent variable was conducted. Main

effect of task difficulty was significant (F(1,15) = 30.15, p<.001). Difficult tasks took significantly more number of clicks than simple tasks. Main effect of age was not significant (p>.05). Interaction of age and task difficulty was not significant (p>.05). Figure 2 shows the means. Just like we did for task-completion time, we looked deeper into the number of clicks made by participants on SERPs and the number of clicks made on websites to see if there is any influence of aging or task difficulty and found exactly similar patterns. That is, the number of clicks on both SERPs and websites was significantly higher for difficult tasks than for simple tasks

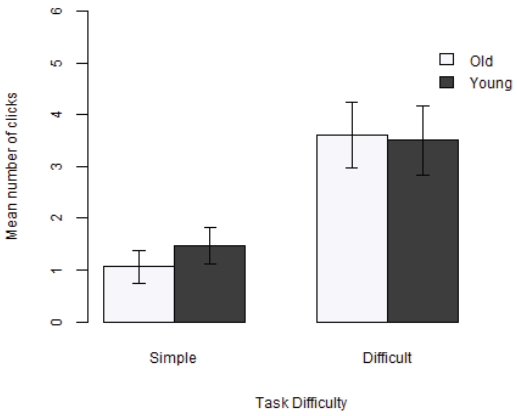

Figure 2. Mean number of clicks (and standard errors) in relation to age and task difficulty

(F(1,15) = 34.6, p<.001, for SERPs and F(1,15) = 11.14, p<.005, for websites respectively). There were no other effects.

4.2.3 Accuracy

A repeated measures ANOVA with age as between-subjects variable, task difficulty as within-subjects variable and mean accuracy as dependent variable was conducted. Main effect of task difficulty was significant F(1,15) = 5.6, p<.05. Accuracy was significantly higher for simple tasks compared to difficult tasks. Main effect of age was not significant (p>.05). However, interaction of age and task difficulty was significant F(1,15) = 5.6, p<.05. Post-hoc tests with Bonferroni correction showed that the old participants were significantly more accurate than young participants in solving simple tasks (p<.05). There was no significant difference in accuracy between young and old for difficult tasks (p>.05). See Figure 3.

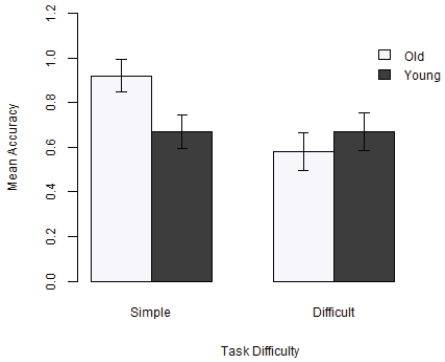

Figure 3. Mean(and standard errors) of accuracy in relation to age and task difficulty

4.2.4 Number of Reformulations

A repeated measures ANOVA with age as between-subjects variable, task difficulty as within-subjects variable and mean number of reformulations as dependent variable was conducted. Main effect of task difficulty was significant (F(1,15) = 23.57, p<.001). Number of reformulations was significantly higher for difficult tasks compared to simple tasks. Main effect of age was significant (F(1,15) = 5.15, p<.05). Young participants made significantly more reformulations than old participants. Interaction of age and task difficulty was also significant (F(1,15) = 4.5, p<.05). Post-hoc tests with Bonferroni correction showed that the number of reformulations made by young participants was significantly higher than old participants for difficult tasks (p<.05) and not for simple tasks (p>.05). Figure 4 shows the means.

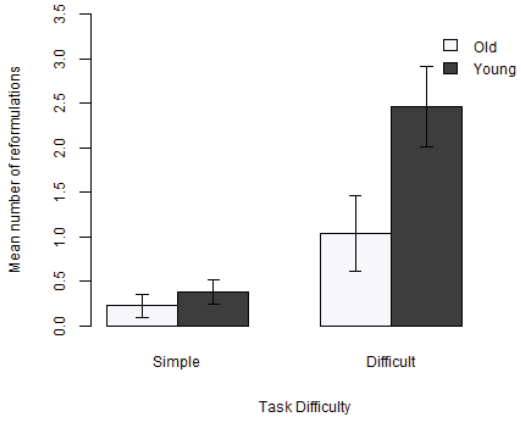

Figure 4. Mean number of reformulations (and standard errors) in relation to age and task difficulty

Summarizing the main behavioral outcomes, we found that in general difficult tasks demanded significantly more time (total, SERPs, and websites), significantly more clicks (total, SERPs and websites), significantly more reformulations and are answered significantly less accurately than simple tasks. Old participants inspected significantly longer the SERPs, produced significantly fewer reformulations with difficult tasks than young participants, and were significantly more accurate than young participants with simple tasks. Our results seem to be in line with those of [10, 12], and do not provide evidence to our hypothesis that old participants are less effective than young participants when it comes to solving difficult information search tasks on the web. We could not find any significant differences among young participants and old participants for difficult tasks. For simple tasks old participants were more accurate than young participants. The only difference that supports our hypothesis was that old participants spent significantly longer time evaluating SERPs than young participants and less frequently leave the SERPs in order to reformulate new queries. It is possible that the older participants develop different search strategies from those of younger participants to perform search tasks and to obtain performance on par with young participants. Therefore, to investigate deeper into age differences in interactions with SERPs, we looked at web-behavior graphs. Web-behavior graphs enable us to see the structural differences between interaction patterns of young and old participants with SERPs.

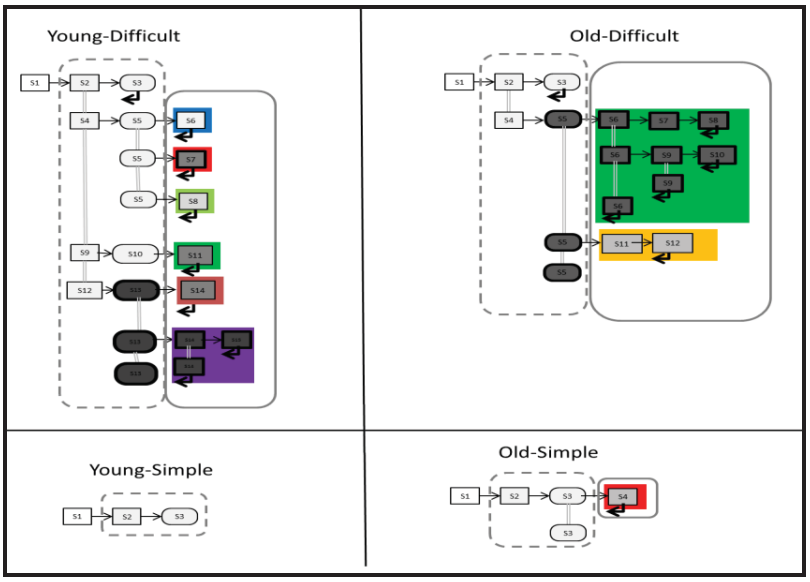

Figure 5. Sample Web Behavior Graphs for young and old participants working on simple and difficult tasks. Different colors indicate different websites, the darkera node, greater the information scent, dotted loop for keyword problem space and continuous loop for link problem space.

4.3 Web-Behavior Graphs

The performance metrics such as task-completion time, number of clicks, accuracy and number of reformulations used to analyze the behavior of young and old participants in Section 4 gave us only a global idea of the participants' behavior. They did not provide us with any insight into the moment by moment cognition that happens, for example between two user clicks. To understand in more detail how participants goals evolved, how they perceived and evaluated the content of SERPs and how they took decisions during the process of solving an information search task, we used Web-Behavior Graphs (WBGs, henceforth), introduced by [4] to visualize the user behavior. These WBGs enable us to see the behavior of the participants at a much finer granularity, i.e., at the level of every action taken by a participant.

During the process of interacting with a search engine, a user can be assumed to be working in a problem space [26]. A problem space consists of a set of states and a set of operators to move from one state to the other, such as initial state, current state, and goal state. Examples of the set of possible states could be google search engine page, SERPs, website, etc. and operators could be clicking on a hyperlink, issuing a query and arriving at a search engine results page, reformulation of query, going back (to search engine results page, or to an already visited website) etc. Initial state is usually the home URL of the search engine. Goal state could be completion of the task. As a participant interacts with the search engine, he moves from one problem state to the other and also from one sub-problem space to the other with the help of various operators. [4] lists four possible problem spaces in the context of interacting with a search engine, two of which we will discuss: link problem space and keyword problem space. Link problem space consists of the set of all valid URLs. Operators are clicking on a hyperlink (textual or imaginal), hitting back button etc. Keyword problem space is the set of all states when the user is typing a query into a search engine. Operators in this space are typing a query, reformulating a query, use of +, and, or, and other modifiers provided by the search engine. Each node in a web-behavior graph represents a different state in the problem space. Each arrow depicts an operator. Oval boxes indicate the SERPs. A downward left arrow indicates that the user is moving back to an earlier state. This earlier state is indicated by a double vertical arrow. Thus time moves from left to right and top to bottom in a WBG. Different colors indicate different websites. A loop around some states indicates the problem space that the user is in. Dotted loop is for keyword problem space and a continuous loop for link problem space. A darker node denotes search results with higher average semantic similarity with the query that generated them. We used three gray levels: light (semantic similarity of 0 to 0.33), medium (semantic similarity of 0.33 to 0.66) and dark (semantic similarity of 0.66 to 1.0) computed using LSA. Figure 5 shows a WBG plotted for one young and one old participant for one representative sample task of each type, simple and difficult. We can make the following observations looking at the WBGs:

- *Task-completion time:* WBGs for young participants are thin and long and those of old participants are broad and short. This is in line with our earlier result that there was no significant impact of age on overall task-completion time.
- *Number of clicks:* Irrespective of the difficulty of task, the number of nodes in a WBG is more or less the same for both young and old participants. This is in line with our earlier result that there was no significant impact of age on number of clicks.
- *Number of reformulations:* WBGs for young participants are longer than those of old participants, especially for difficult tasks. This matches our earlier result that young participants make more reformulations than old participants, especially for difficult tasks.
- *Simple vs Difficult:* We can see clearly that the number of nodes and the number of websites visited in WBGs for simple tasks is far less than the number of nodes and the number of websites visited in WBGs of difficult tasks. This is also true for both young and old participants. This is in line with our earlier result that the performance of both

young and old participants on simple tasks is better than on difficult tasks (task-completion time, number of clicks and number of reformulations).

The observations so far are in line with the findings from the behavioral study. We can still make two new observations from Figure 5. First, the number of unique websites visited by young participants is much greater than old participants for a given task, especially in difficult category. Young participants do not explore the content of a website beyond what is provided by a search engine whereas old participants explore the content of a website deeper by clicking on hyperlinks within the website. This observation leads us to a possible explanation for lack of significant differences between young and old participants for both time and clicks. If we look at the time spent per unique website and number of clicks per unique website instead of total time on all websites combined and total number of clicks on all websites combined, it is highly likely that we might find a significant difference. Old participants might spend significantly more time per website than young participants, especially for difficult tasks. Similarly, old participants seem to make significantly more clicks per website than young participants, especially for difficult tasks. However, we do not have sufficient data at that granularity to verify the above hypothesis.

Second, inspecting the WBGs in further detail, we got the impression that the ratio of the number of dark nodes (medium and dark) to the number of light nodes (light) is higher for old participants compared to young participants which could mean that the old participants tend to click more often than young participants on search engine results or websites that are higher in the average semantic similarity value (of the ten search results with the query). Also, we observed that the darker nodes appear much earlier in time for old participants than for young participants; the reason for which could be that the old participants used better queries that generated SERPs with higher LSA much earlier than young participants. These speculations trigger a number of questions. Do old participants really click less often on hyperlinks with low information scent than young participants? Do old participants indeed generate search engine results with higher information scent sooner than young participants? We try to address these questions along with our second research question: can cognitive models of web-navigation be used to model and predict user interactions with search engine, in the next section. As far we know, this is the first empirical study testing the usefulness of cognitive models of web-navigation on user interactions with search engines.

5. MODELING USER INTERACTION WITH SERPs

In this section, we explore the feasibility of using cognitive models of web-navigation using CoLiDeS (because of its simplicity and ease of implementation), in modeling user interaction behavior with SERPs. In this work, we do not make any modifications to modeling to reflect the behavioral differences caused by aging. On the contrary, our aim is to first investigate to what extent the CoLiDeS model, without making any modeling changes, is able to simulate different groups of participants. We will examine some of the unanswered questions raised in the previous section. We will do this step by step: We first start with investigating what role information scent plays in choices made by users by looking at the frequency of user clicks in relation to search engine result's LSA values in Section 5.1. We next look at the progression (increase or decrease) of the average LSA value of search engine results across multiple cycles of reformulations and its impact on user behavior in Section 5.2. We describe the steps involved in running simulations of CoLiDeS and making predictions on SERPs in Section 5.3. We match the simulations with actual user data in Section 5.4.

5.1 Role of information scent on user interaction with SERPs

In order to understand the role information scent plays in decisions that users take when navigating on the web, authors in [15] computed the number of times a hyperlink with a particular rank is clicked. Two types of ranks were used: ranks produced by SNIF-ACT 1.0 and those produced by a model which is solely based on the position of a search result. We did a similar analysis and compared the number of times a search engine result is clicked by both young and old participants against the rank of the search result as computed by CoLiDeS. CoLiDeS ranks search engine results from top to bottom based on their semantic similarity with the query that generated them. To compute semantic similarity, we used the title and blurb of each search result provided by Google's search engine. For running LSA on French material, we used the French-Monde-Unicode space provided by University of Colorado, Boulder[2]. This semantic space was unfamiliar with words from manga domain and therefore we focused only on health. We assume that a query is the best representation of the goal at that moment. Therefore, we use query as the basic unit for the following analysis. For each participant and for each query generated by the participant, LSA ranks of the search engine results corresponding to that query were computed. A search engine result with maximum LSA value will get LSA Rank 1, the search engine result with the next highest LSA gets LSA Rank 2 and so on.

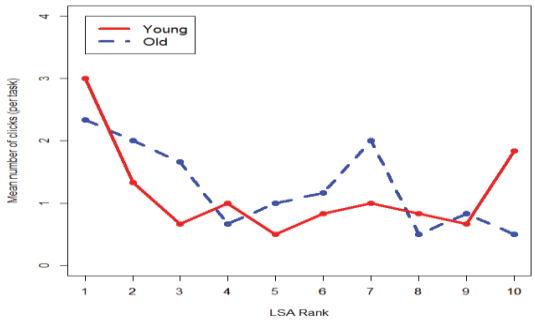

Figure 6. The mean frequency of SERPs chosen by participants in relation to their LSA Rank.

If a user clicks on a search engine result which is 4th highest in terms of LSA, then LSA Rank 4 gets one count. In this manner, we counted the number of times a user clicks on each of the LSA ranks. This process was repeated, separately for all young and all old participants. Figure 6 shows the resulting graph. A search engine result with the highest LSA rank was chosen on an average 3 times by young participants and 2.34 times by old participants. Similarly, a search engine result with second highest LSA rank was chosen on an average 1.3 times by young participants and 2 times by old participants. Spearman's rho revealed a statistically significant relationship between LSA rank and frequency of user

[2] http://autocww2.colorado.edu/

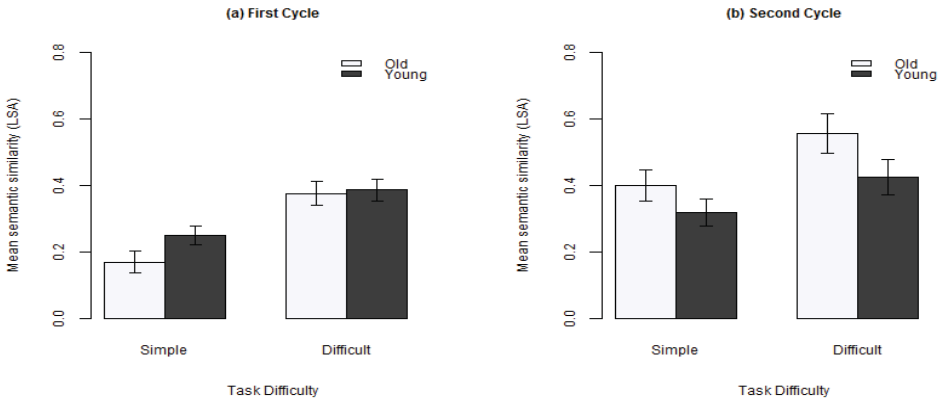

Figure 7. Mean LSA value (and standard errors) of SERPs in (a) first cycle and (b) second cycle in relation to age and task difficulty

clicks r_s = -0.72, n=10, p<.05 for old and a non-significant relationship r_s = -0.21, n=10, p>.05 for young. A Fisher's r-to-z transformation showed a significant difference between the above two correlations (z=10.65, p<.01).

The higher negative correlation for old participants showed that old participants tended to click more often on search engine results with high LSA rank than young participants. A deeper analysis with task difficulty as a factor showed that this pattern was true only for difficult tasks (r_s = -0.75, n=10, p<.01 for old and r_s = -0.17, n=10, p>.05 for young, Fisher's z=12.3, p<.01) and not for simple tasks (r_s = -0.10, n=10, p>.05 for old and r_s = -0.11, n = 10, p>.05 for young, Fisher's z=0.15, p>.05). This empirically and affirmatively connects to one of the unanswered questions from the WBGs in Section 4.3: Do old participants really click more often on hyperlinks with high information scent than young participants?

5.2 Progression of LSA across multiple reformulations

In this analysis, we were interested in answering the following questions: How does mean semantic similarity of SERPs change across multiple reformations? Does the second query for a given task generate SERPs with higher mean semantic similarity than the first query? If yes, is there an impact of age or task difficulty on this pattern? In order to answer these research questions, we conducted a 2 (Cycle: First vs. Second) X 2 (Task Difficulty: Simple vs. Difficult) X 2 (Age: Young vs. Old) repeated measures ANOVA with cycle and task difficulty as within-subjects variables and age as between-subjects variable. Mean semantic similarity between the SERPs and the query that generated them was our dependent variable. We restricted our analysis to the first and second cycles of reformulations. Main effect of cycle was significant F(1,7) = 31.6, p<.001. The queries in second cycle generated SERPs with significantly higher mean semantic similarity than queries in first cycle. Main effect of task difficulty was significant F(1,7) = 20.43, p<.005. Queries for difficult tasks generated SERPs with significantly higher mean semantic similarity than queries for simple tasks. Main effect of age was not significant (p>.05). Interaction of cycle and age was significant F(1,7) = 11.0, p<.05. The difference in mean LSA value of SERPs between first and second cycles was more prominent for old than for young. Interaction of cycle and task difficulty was not significant (p>.05). Interaction of task difficulty and age was not significant (p>.05). Interaction of cycle, task difficulty and age was also not significant (p>.05). Figure 7 shows the means.

So far we looked at how age, task difficulty and cycle interact with information scent of search engine result pages and user behavior. We first saw that information scent strongly drives user interactions with search engine result pages. Old participants generally click more frequently on those search results which have high semantic similarity compared to young participants, more so for difficult tasks. Next, we investigated how semantic similarity progresses as participants reformulate their queries and found that the queries in the second cycle were significantly much better than the queries in the first cycle, if we take the mean LSA value of the SERPs generated as a metric. The mean LSA value of SERPs was significantly higher in the second cycle than first cycle. This was true especially for old participants. Also, the mean LSA value of SERPs was significantly higher for difficult tasks compared to simple tasks. These results are encouraging enough for us to extend cognitive models of web-navigation to predict user interactions with search engine result pages. Because information scent influenced user behavior more for difficult tasks than for simple tasks, we hypothesize that the model predictions would be significantly better for difficult tasks compared to simple tasks. In the following section, we first describe how to run CoLiDeS model on search engine results.

5.3 Simulation of CoLiDeS on SERPs

We ran simulations of CoLiDeS on search engine result pages using the same methodology followed by Karanam et al. [20] on a mock-up website on the human body. Here, we consider each SERP as a page of a website. And each of the search engine results as a hyperlink within a page of a website. The problem of predicting which search engine result to click is now equivalent to the problem of predicting which hyperlink to click within a page of a website. Therefore, the process of computing information scent and predicting which search engine result to click remains the same as in [20]. For the time being, we used a user-generated query as a representation of local goal or the understanding of the user at any point of time and semantic similarity values were computed from it. Just like in [20], we used the process of elaborating the goal (user query) and the search engine results (title + blurbs) to simulate the cognitive processes of activation of semantically related terms to a piece of text that happens in our working memory (through spreading activation mechanism). These elaborations are known to assist in better comprehension of

material [21]. We are now ready to describe the steps we follow in simulating CoLiDeS on SERPs:

a) *Select a user task:* From the set of tasks in Table 1 from Experiment, pick one. Say, our task is (Task 5 from Table 1) '*Madame Martin, âgée de 60 ans, souffre de douleurs dans la poitrine et de difficultés respiratoires. Qu'est ce que vous pensez, elle souffre a quelle maladie?*'

b) *Select a search query:* Select the first search query used by a participant for the task selected in (a). Suppose the search query is '*douleurs dans la poitrine et difficultés à respirer'*

c) *Elaborate the user task:* User task is elaborated with words that are its nearest semantic neighbours. We used LSA's nearest neighbour analysis to pick those words that occurred at least 50 times in the corpus and that had a semantic similarity value of at least 0.5 with the goal. Using this method, we got the following elaborated representation of the task: 'M*adame Martin âgée de 60 ans souffre de douleurs dans la poitrine et de difficultés respiratoires qu'est ce que vous pensez elle souffre à quelle maladie vous votre avez ruin aurez vos'*

d) *Elaborate the search query:* Using the methodology described in c), user query was elaborated. The elaborated user query for our example is '*douleurs dans la poitrine et difficultés à respirer douleurs poitrine'*

e) *Generate the search engine result page corresponding to the search query:* Using the search engine and the user query, generate the search engine result page, a list of 10 titles and 10 blurbs as shown by the search engine. Save the 10 urls for reference. We will use the first title + blurb combination for illustrating our example: *Douleur thoracique, difficulté à respirer [Résolu] - Santé-Médecine (heading) ... douleur thoracique gauche difficulté à respirer et nausée je rappelle ..... électrocardiogramme normal n'élimine pas une angine de poitrine*. A complete list of hyperlink + blurb combinations is given in Appendix I.

f) *Elaborate the titles + blurbs combination:* Similar to (c) and (d), elaborate each of the ten title + blurb combinations, by adding words closest in similarity to them. The elaborated representation of the title + blurb combination of our example in e) is as follows: '*douleur thoracique difficulté à respirer résolu santé médecine douleur thoracique gauche difficulté à respirer et nausée je rappelle électrocardiogramme normal n'élimine pas une angine de poitrine à gauche*'. The words added to the title + blurb combination for elaboration are shown within brackets in Appendix I.

g) *Compute semantic similarity between elaborated query and the elaborated titles + blurbs combination:* Using LSA, we computed the semantic similarity between the elaborated query and the elaborated titles + blurbs combinations. For our example task and the query, we obtained the following semantic similarity value: 0.22. Repeating this process for the remaining 9 title + blurb combinations gave us the following LSA values: 0.33, 0.12, 0.4, 0.48, 0.47, 0.4, 0.52, 0.12 and 0.47.

h) *Prediction:* Following Blackmon et al. 2007, all those search engine results that have a semantic similarity of 0.8 times the maximum semantic similarity are considered predictions by the model. That is, the model predicts that the user is likely to click on any of these hyperlinks with equal probability. The maximum semantic similarity in our example is obtained for Link 8 (0.52). Links 5 (0.48), Link 6 (0.47) and Link 10 (0.47) are all above the 0.8 threshold. Therefore, the model predicts that any of these four links can be clicked by the user with equal probability.

i) *Repeat:* Repeat this process for all queries of the task in (a) and for all tasks for a participant and finally for all participants.

After running simulation steps a) to i), we will have model-predictions on all queries of all tasks and all participants. Using the actual user behavior data collected in the experiment, we test the efficacy of the model predictions in the next section: that is, to what extent the model predictions match with actual user clicks?

5.4 Efficacy of CoLiDeS on SERPs

We compute efficacy of model using two metrics: number of times model predictions match with actual user behavior computed for each participant and the total percentage of matches computed on all participants data.

5.4.1. Number of Matches per participant

For each query and the corresponding search engine results, if a user click matches with the model prediction for that query, we consider it as a match. This is repeated for all queries of a task.

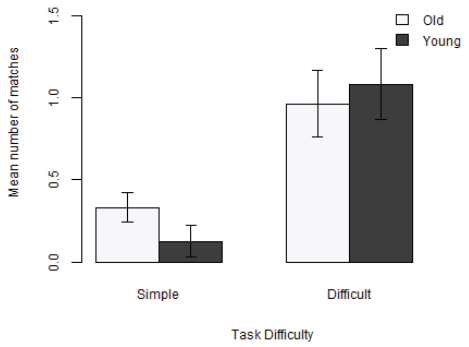

Figure 8. Mean number of matches (and standard errors) between model predictions and actual user clicks in relation to age and task difficulty

Using this methodology, the number of matches per participant was computed separately for young and old participants under two task conditions: simple and difficult. Figure 8 shows the results of this analysis. A repeated measures ANOVA with age as between-subjects variable, task difficulty as within-subjects variable and mean number of matches per participant as dependent variable was conducted. Main effect of task difficulty was significant ($F(1,15) = 24.96$, $p<.005$). Number of matches was significantly higher for difficult tasks as compared to simple tasks. Main effect of age was not significant ($p>.05$). Interaction of age and task difficulty was not significant ($p>.05$).

5.4.2. Total percentage of matches

For each query, the search engine results clicked by a participant were compared with the search engine results predicted by the model. If a search engine result predicted by the model is also clicked by a participant, it is considered as a match. This process was repeated for all the queries of a task, for all tasks and for all participants. We then looked at the total percentage of all the clicks made by all the participants that match with the model-predictions as shown in Table 2. We can see that the percentage of

actual user clicks that match with model-predicted clicks is higher for difficult tasks (44.83% for old, 41.94% for young), compared to that of simple tasks (39.13% for old, 18.75% for young).

Table 2. Percentage of actual user clicks that match with model predictions in relation to age and task difficulty

	Simple		Difficult	
	Total clicks	**Number of Matches (%)**	**Total clicks**	**Number of Matches (%)**
Old	23	9 (39.13)	58	26(44.83)
Young	16	3 (18.75)	62	26(41.94)

A chi square test of goodness of fit gave a near significance value ($\chi 2 = 3.43$, $p \sim 0.06$). Combining the two outcomes (from Figure 8 and Table 2), we can say that model predictions are significantly more accurate for difficult tasks than for simple tasks. This is because difficult tasks require users to activate or use their knowledge from memory much more than simple tasks. The match percentage is a function of both actual user behavior and the accuracy of the model. Since we used the same modeling approach for both young and old participants, the differences we see in match percentages can be only be because of the differences in actual behavior of young and old participants.

6. CONCLUSIONS AND DISCUSSION

In this paper, we identified two major limitations of cognitive models of web-navigation developed so far. First, they do not characterize the process of information search completely. A typical information search process usually starts from the search engine and involves generating queries, evaluating search results and choosing one or more results from the search engine's output list, comprehending the content of the chosen links, navigating the chosen links deeper using the hyperlinks within them if necessary and reformulating queries to generate a fresh set of search results. There are clearly two main parts to this entire process: interactions with a search engine and interactions with a website. The cognitive models of web-navigation developed so far look at only interactions with a website and do not account for interactions with a search engine. Second, they do not take into account the effect of aging on cognitive processes involved in the process of information search. Several cognitive processes such as memory, attention, problem solving, reasoning, comprehension and decision making are involved when interacting with the internet. These cognitive processes are in turn affected by several cognitive factors, of which we focused on age. With aging, a natural decline in fluid intelligence characterized by a decrease in processing speed, cognitive flexibility or ability to switch processing strategies, attentional control and visuospatial span occurs. However, crystallized intelligence characterized by prior knowledge, experience and vocabulary skills is known to remain constant or even increase in some cases. While there are several studies that investigate the role played by these age-related changes on navigation behavior of old people (old people are known to explore less and exploit more, take longer to finish tasks and are less accurate than young people), most of them are focused on navigation with websites and very few are focused on interactions with search engines. Prior research is inconclusive about performance differences between young and old users when it comes to the impact of task difficulty on interacting with a search engine.

We addressed the above two limitations, by using partial data from an experiment conducted by [10], that is, six information retrieval tasks (three simple and three difficult) from health domain. We found that in general difficult tasks demand significantly more time (total, SERPs, and websites), significantly more clicks (total, SERPs and websites), significantly more reformulations and are answered significantly less accurately than simple tasks. Older persons inspect the SERPs significantly longer, produce significantly less reformulations with difficult tasks than younger persons, and are significantly more accurate than younger persons with simple tasks.

In order to understand the information search patterns of young and old participants more deeply, we looked at their Web-Behavior Graphs. WBGs not only confirmed our main behavioral outcomes but also gave us a potential explanation for the lack of significant differences in the performance measures of task-completion time and clicks between young and old participants for difficult tasks. We considered the total time spent and total number of clicks on all websites clicked by a participant. Instead, if we could have looked at the amount of time spent and number of clicks made per each website accessed by a participant, it could have been more useful. From the WBGs, we raised two more interesting questions: Do old participants really click less often on hyperlinks with low information scent than young participants? Do old participants indeed generate search engine results with higher information scent sooner than young participants?

We used a frequency plot of the number of clicks and LSA rank of a search engine result to empirically prove that old people click more often on search engine results with high LSA value than young people. When we did this analysis separately for simple and difficult tasks, we found that this was true, for difficult tasks only. To empirically answer the second question, we looked at how average LSA value of SERPs progresses across two cycles of reformulations (first and second). Queries in the second cycle generated SERPs with significantly higher LSA than queries in first cycle. This difference was more prominent for queries generated by old people than by young people. Also, queries used for difficult tasks generated SERPs with significantly higher LSA value than queries used for simple tasks. Finally, we used CoLiDeS to model and predict user interactions with search engines. We ran simulations and used the model predictions from the simulations to match with the actual user data. We found that the number of matches per participant was significantly higher for old people compared to young people, especially for difficult tasks. Also, percentage of total user clicks that match with model predicted clicks was higher for difficult tasks: close to 45% for old people and 42% for young people compared to simple tasks: 39% for old people and 19% for young people. The actual number of clicks made by young people for simple tasks is much less than the actual number of clicks made by old people on simple tasks. That could mean that young people found the answer to the simple questions without clicking on any search results (i.e., from the blurbs) more often than old people. These percentages fall within the same range as obtained by earlier studies on navigation within websites: 37.6% by [20] and 46.9% by [19]. This confirms the hypothesis that the cognitive processes involved in deciding to click on a hyperlink when navigating within websites and the cognitive processes involved in deciding to click on a particular search result are the same.

In summary, we made two main contributions in this paper, first, we added to the understanding of the research community on the

differences in navigation behavior between young and old people when it comes to interacting with search engines. We found that CoLiDeS model could predict roughly 40% of clicks made by old participants (not much difference with young participants). There is however scope for improving this percentage further by making some changes to modeling in order to reflect the behavioral differences in web-navigation caused by aging, such as using different semantic spaces to reflect the differences in crystallized knowledge between young and old people. Second, we made the first steps towards using cognitive models of web-navigation, which were until now used only on websites, for modeling and predicting user interaction behavior with search engines.

7. FUTURE DIRECTIONS

There are several possible extensions that can be made to the work presented in this paper. Our study did not involve questions that required the user to navigate deeply into a website to find an answer. A more granular recording of time and clicks (per unique website) would be useful to look more deeply at the performance differences between young and old people for difficult tasks. It would be interesting to see how the model performance changes if we use the main goal instead of the query to compute semantic similarities. The current research can lead to several applications in developing support tools for navigation for people in need such as old people. For example, Chin et al. [6], showed that providing link recommendations could be a way to help old people utilize their higher crystallized knowledge and reduce cognitive effort required to process irrelevant hyperlinks.

8. ACKNOWLEDGEMENTS

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9. REFERENCES

[1] Aula, A. 2005. User study on older adults' use of Web and search engines. *Universal Access in the Information Society*, *4*(1), 67–81.

[2] Blackmon, M. H., Kitajima, M. and Polson, P.G. 2005. Tool for accurately predicting website navigation problems, non-problems, problem severity, and effectiveness of repairs. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (Oregon, US, 2005), ACM, New York, 31-40.

[3] Blackmon, M. H., Mandalia, D. R., Polson, P. G. and Kitajima, M. 2007. Automating usability evaluation: Cognitive walkthrough for the web puts LSA to work on real-world HCI design problems. In Landauer, T., McNamara, D., Dennis, S., and Kintsch, W. (Eds.), *Handbook of latent semantic analysis*, L. Erlbaum Associates, Mahwah, NJ, 345-375.

[4] Card, S., Pirolli, P, Van Der Wege, M., Morrison, J., Reeder, R., Schraedley, P. et al. 2001. Information scent as a driver of Web Behavior Graphs: Results of a protocol analysis method for web usability. In *Proceedings of the SIGCHI conference on Human factors in computing systems,* (Seattle, USA), ACM, New York, 498-505.

[5] Chevalier, A., Dommes, A., Martins, D. and Valerian, C. 2007. Searching for information on the web: Role of aging and ergonomic quality of website. In *International Conference on Human-Computer Interaction. Interaction Design and Usability*, (Beijing, China), Springer-Verlag, Berlin, Heidelberg, 691-700.

[6] Chin, J., Fu, W. T. and Kannampallil, T. 2009. Adaptive information search: age-dependent interactions between cognitive profiles and strategies. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, (Boston, USA). ACM, New York, 1683-1692.

[7] Chin, J. and Fu. W.T. 2010. Interactive effects of age and interface differences on search strategies and performance. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, (Atlanta, USA), ACM, New York, 403-412.

[8] Chin, J., Payne, B., Fu, W-T., Morrow, D. and Stine-Morrow, E.A. L. (2012). Information foraging in the unknown patches across the life span. In N. Miyake, D. Peebles, & R. P. Cooper (Eds.), *Proceedings of the 34th Annual Conference of the Cognitive Science Society*. (Austin, TX, USA. Cognitive Science Society. 1404-1409.

[9] Chin, J. and Fu, W. T. 2012. Age differences in exploratory learning from a health information website. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,* (Austin, USA), ACM, New York, 3031-3040.

[10] Chin, J., Chevalier, A., He, J. and Fu, W.T. (2014). Linking knowledge in the head to knowledge in the world: Age differences in web exploration with the search engine. *Cognitive Aging Conference*. (Atlanta, GA, USA).

[11] Dinet, J., Brangier, E., Michel, G., Vivian, R., Battisti, S. and Doller, R. 2007. Older people as information seekers: Exploratory studies about their needs and strategies. In *Universal Access in Human Computer Interaction. Coping with Diversity* (Beijing, China), Springer-Verlag, Berlin, Heidelberg, 877-886.

[12] Dommes, A., Chevalier, A. and Lia, S. 2011. The role of cognitive flexibility and vocabulary abilities of younger and older users in searching for information on the web. *Applied Cognitive Psychology*, *25*(5), 717-726.

[13] Eastman, J. K.. and Iyer, R. 2004. The elderly's uses and attitudes towards the Internet. *Consumer Marketing*, *21*(3), 208-220.

[14] Fu, W. T. and Gray, W. D. 2006. Suboptimal tradeoffs in information seeking. *Cognitive Psychology*, *52*(3), 195-242.

[15] Fu, W. T. and Pirolli, P. 2007. SNIF-ACT: A cognitive model of user navigation on the World Wide Web. *Human–Computer Interaction*, *22*(4), 355-412.

[16] Grahame, M., Laberge, J. and Scialfa, C. T. 2004. Age differences in search of web pages: The effects of link size, link number, and clutter. *Human Factors*, *46*(3), 385-398.

[17] Horn, J. L. 1982. The theory of fluid and crystallized intelligence in relation to concepts of cognitive psychology and aging in adulthood. In Craik, F. I. M. and Trehub, S. E. (Eds.), *Aging and cognitive processes* (pp. 847–870). New York: Plenum Press.

[18] Horn, J. L. and Cattell, R. B. 1967. Age difference in fluid and crystallized intelligence. *Acta Psychologica*, *26*, 107–129.

[19] Juvina, I., and van Oostendorp, H. 2008. Modeling semantic and structural knowledge in Web navigation. *Discourse Processes*, *45*(4-5), 346-364.

[20] Karanam, S., van Oostendorp, H. and Indurkhya, B. 2012. Evaluating CoLiDeS+ Pic: the role of relevance of pictures in user navigation behaviour. *Behaviour & Information Technology*, *31*(1), 31-40.

[21] Kintsch, W. *Comprehension: A paradigm for cognition*. Cambridge University Press, 1998.

[22] Kitajima, M, Blackmon, M. H. and Polson, P. G. 2000. A comprehension-based model of web navigation and its application to web usability analysis. In Mc Donald, S., Waern, S. and Cockton, G. *People and Computers XIV—Usability or Else!*, Springer, London, 2000, 357-373.

[23] Landauer, T. K., Foltz, P.W. and Laham, D. 1998. An introduction to latent semantic analysis. *Discourse Processes*, *25*(2-3), 259-284.

[24] Mitzner, T. L., Boron, J. B., Fausset, C. B., Adams, A. E., Charness, N., Czaja, S. J. et al. 2010. Older adults talk technology: Technology usage and attitudes. *Computers in Human Behavior*, *26*(6), 1710-1721.

[25] Miller, C. S. and Remington, R. W. 2004. Modelling Information Navigation: Implications for Information Architecture. *Human-Computer Interaction*, *19*(3), 225-271.

[26] Newell, A. and Simon, H. A. 1972. *Human Problem Solving*. Englewood Cliffs, Prentice-Hall, NJ.

[27] Olston, C. and Chi, E. H. 2003. ScentTrails: Integrating browsing and searching on the Web. *ACM Transactions on Computer-Human Interaction*, *10*(3), 177-197.

[28] Pak, R. and Price, M. M. 2008. Designing an information search interface for younger and older adults. *Human Factors*, *50*(4), 614–628.

[29] Pirolli, P. and Card, S. 1999. Information foraging. *Psychological Review*, *106*(4), 643-675.

[30] Pirolli, P. and Fu, W. T. 2003. SNIF-ACT: A model of information foraging on the World Wide Web. In *User Modeling* (Johnstown, PA, USA), Springer-Verlag, Berlin, Heidelberg, 45-54.

[31] Sharit, J., Hernández, M. A., Czaja, S. J. and Pirolli, P. 2008. Investigating the roles of knowledge and cognitive abilities in older adult information seeking on the web. *ACM Transactions on Computer-Human Interaction*, *15*(1), Article 3.

[32] Slegers, K., van Boxtel, M. and Jolles, J. 2009. Effects of computer training and internet usage on cognitive abilities in older adults: a randomized controlled study. *Aging clinical and experimental research*, *21*(1), 43-54.

[33] Van Oostendorp, H., Karanam, S. and Indurkhya, B. 2012. CoLiDeS + Pic: a cognitive model of web-navigation based on semantic information from pictures. *Behaviour & Information Technology*, *31*(1), 17-30.

[34] Wang, J. and Kaufman, A. S. 1993. Changes in fluid and crystallized intelligence across the 20- to 90-year age range on the K-BIT. *Psychoeducational Assessment*, *11*(1), 29–37.

[35] Zaphiris, P., Kurniawan, S. and Ghiawadwala, M. 2007. A systematic approach to the development of research-based web design guidelines for older people, *Universal Access in the Information Society*, *6*(1), 59-75.

9. APPENDIX-I

Heading and Blurb of search engine results (*words added after elaboration*)
douleur thoracique difficulté à respirer résolu santé médecine douleur thoracique gauche difficulté à respirer et nausée je rappelle électrocardiogramme normal n'élimine pas une angine de poitrine (*je gauche*)
douleur dans la poitrine d'origine non cardiaque e-sante douleur dans la poitrine d'origine non cardiaque bonsoir j'ai 25 ans cela fait 1 mois maintenant que j'ai du mal à respirer sa survient que au moment du coucher quand je m'allonge dans mon lit je dois difficulté pour respirer à fond (*je suis*)
comprendre difficultés à respirer guide coeur sein difficulté à respirer essoufflement sensation d'étouffement est ce bonjour j'ai une douleur ce qui me fait mal à l'effort en montant une cotte (*j' ai avais mes*)
la douleur thoracique transfert de connaissances coeur c'est une douleur ressentie à la hauteur de la poitrine elle provient du coeur parfois à heure fixe accompagnée de difficultés respiratoires elle signifie en (*elle*)
infarctus du myocarde les symptômes qui doivent alerter les victimes ressentent aussi une difficulté à respirer être l' anxiété le stress une douleur osseuse qui se projette au niveau de la poitrine (*victimes*)
respiration difficile maladies sante a l'angine de poitrine ou angor correspond à une douleur respiration difficile difficulté respiratoire trouble respiratoire du mal à respirer ( )
embolie pulmonaire planète santé caillot de sang elle se manifeste par une douleur dans la poitrine d'apparition brutale associée à une difficulté à respirer dernière mise à jour (*elle*)
gêne respiratoire de l'adulte Docteurclic comme il s'agit alors d'une douleur dans la poitrine parfois enfin les deux phénomènes sont liés à la fois avoir du mal à respirer et avoir une douleur vague et diffuse ( )
difficulté respiratoire douleur thoracique vertige asthme voila j'ai 18 ans et depuis déjà 1 semaine et demi j'ai des difficulté une forte douleur au thorax et au sein gauche sensation de poignard ou que sa tire symptôme excepté les difficulté a respirer qui durai 1 mois environ (*j'ai*)
douleur de la poitrine Doctissimo les douleurs de la poitrine sont fréquentes et peuvent avoir des dans le bras gauche la mâchoire des difficultés respiratoires des nausées (*gauche*)