Extending Predictive Models of Exploratory Behavior to Broader Populations

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Abstract. We describe the motivation for research aimed at extending predictive cognitive modeling of non-expert users to a broader population. Existing computational cognitive models have successfully predicted the navigation behavior of users exploring unfamiliar interfaces in pursuit of a goal. This paper explores factors that might lead to significant between-group differences in the exploratory behavior of users, with a focus on the roles of working memory, prior knowledge, and information-seeking strategies. Validated models capable of predicting novice goal-directed exploration of computer interfaces can be a valuable design tool. By using data from younger and older user groups to inform the development of such models, we aim to expand their coverage to a broader range of users.

Keywords: Cognitive modeling, information foraging, usability testing, accessibility, interface design, older users.

1 Introduction

Cognitive modeling, most notably keystroke-level modeling (KLM) as originally formulated by Card, Moran, and Newell [1], has proven to be highly predictive of the times taken for skilled performance of a variety of tasks. KLM, and its more complex relative, GOMS, has been extensively validated and widely applied. Gray et al [2], Callander and Zorman [3], John and Kieras [4], Luo and John [5], and Knight, et al [6], illustrate the variety of successful uses of this modeling approach.

More recently, several models of novice goal-directed information search on the Web have been developed and shown to predict human behavior. Our work extends existing research by focusing on comparisons of younger and older users. In this paper, we discuss cognitive factors that might impact performance on such tasks and lead to differences between older and younger groups. We seek to understand whether current theories of goal-directed exploratory behavior, as implemented in existing

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models, apply broadly, and what (if any) enhancements to current models will better predict the behavior of users of different ages.

2 Modeling Skilled Behavior

HCI professionals are generally capable of constructing keystroke-level models by hand but this can become tedious if the design is complex. The correct placement of mental operators is also error prone undercutting model accuracy. To increase modeling efficiency and decrease modeling errors, John et al. created CogTool [7] to support the storyboarding of designs, the demonstration of tasks against those designs, and the resultant automatic generation of accurate models.

Models of expert performance have begun to develop a more nuanced representation of users that incorporates differences between groups. Daily et al [8] applied personalized models to explain the performance of individual subjects across two different tasks. Further work by Rehling et al. [9] applied individual models based on performance in one task to predict performance in a second task.

Jastrzembski and Charness [10] developed 'younger' and 'older' GOMS models, based on cognitive parameters suggested by prior literature. Two mobile phone tasks were modeled: dialing a number and sending a text message. The models predicted performance differences observed in an older and younger group of participants performing these tasks. These parameters were later mapped to equivalent ACT-R parameters, and again the age-specific parameters produced a better fit to the data than the default ACT-R parameters [11].

In further work, John and Jastrzembski [12] explored a series of models built using CogTool. The most successful model for the older adult group revisited the written instructions in the dialing task more frequently to extract the next set of digits to dial. The best models were able to detect statistically significant differences between the age groups, though the match to observed times (within 10-20% of observed times) was less good than that of the original hand-built GOMS models (within 5% of observed times). Awareness of the role of working memory in task performance proved instrumental in the production of high quality models of skilled performance.

3 Modeling Exploratory Behavior

Navigating an unfamiliar interface can be described using the information foraging framework initially developed to describe the behavior of people navigating the Web [13], [14], [15], and subsequently used to model the behavior of users in other information-rich environments such as debugging unfamiliar code in an integrated development environment [16], [17]. The basic idea underlying information foraging is that a user evaluates which item (e.g., a link) to select next by assessing the semantic relationship between the goal (expressed as a series of linguistic tokens) and the item (similarly expressed as a series of tokens). This semantic relationship is characterized by its "information scent" with higher scent items being more likely to be selected than lower scent items. Various strategies for deciding when an item has a high enough scent to follow it, what to do when no links on the current page have a high enough scent, how rapidly the memory of having selected an item decays, and so on, can all be modeled within a general purpose cognitive architecture such as ACT-R [18]. The computation of information scent is based on an underlying text corpus and is roughly a measure of the degree to which the goal and the item are "near" each other in the corpus.

Several computational cognitive models of information seeking on the Web, incorporating information foraging theory, have been shown to make good predictions of users' interaction with Web sites [19], [20]. Our approach to modeling exploratory behavior is to build on CogTool-Explorer [21], a version of CogTool that implements novice goal-directed exploration through information foraging.

CogTool-Explorer uses the ACT-R cognitive model [22], and incorporates SNIF-ACT 2.0, a computational cognitive model of how people use information scent cues to make navigation decisions on the Web [23]. In SNIF-ACT, items on a Web page are evaluated one by one, and a decision is made either to "satisfice" (choose the best seen so far), look further, or go back. In CogTool-Explorer, headings, and then items within headings, are evaluated in the order dictated by Halverson and Hornoff's Minimal Model of Visual Search [24].

3.1 Calculating Information Scent

Successful modelling of novice behaviour depends crucially on the ability to make human-like judgments of the similarity between a goal and an item in a user interface. A number of algorithms have been explored, including latent semantic analysis (LSA), pointwise mutual information, generalized LSA, and Vectorspace approaches. All of these algorithms depend on the presence of a large corpus of text that represents the user's knowledge, and their performance improves as the corpus size increases.

By default, CogTool-Explorer uses LSA calculations based on the TASA corpus. TASA is a corpus often used for LSA calculations, and incorporates texts that a first year college student would be expected to have read. Blackmon's AutoCWW also used this approach. Other research has explored corpora based on material found on the Web, on Wikipedia, or New York Times articles.

Pointwise mutual information is a simpler measure that captures how likely it is to find word A in a text given that it contains word B, adjusting for the frequency of A and B in the corpus. It has the advantage that the corpus can be more easily extended and scaled. For large corpora, several studies have found it to perform better than LSA on similarity judgements [25]. Stone et al [26] report that the Vectorspace model performed better than LSA in predicting eye movements in a web search task.

More sophisticated scent calculations have also been developed. The CoLiDes model of web navigation [27] integrates five factors to assess information scent: semantic similarity based on LSA, elaboration of terms to include similar terms, word frequency, previous experience, and literal matching between the goal and the user interface object being assessed.

3.2 The Role of Between-Group Differences

If models of information seeking are to be useful to designers (who must design for a range of user abilities), the underlying models must be broadly applicable. However, little is known about between-group differences in information foraging behavior. Blackmon et al's experiments [19], upon which both the Auto-CWW and CogTool-Explorer models are based, were performed with college students. The evaluations of the SNIF-ACT theory were based on data gathered from researchers and academics, and from individuals recruited on the web about whom little is reported, except that they were able to install specialized software in order to participate in the experiment. It is plausible that these models represent strategies and approaches primarily used by relatively young people with high levels of cognitive function.

Age and cognitive skills are particularly interesting dimensions to study. Older adults are a significant, and growing, group of technology users that are often under-represented in both research and design. They also tend to be a more heterogeneous group, in part due to the variable effects of age-related changes in cognitive, physical and sensory abilities. An important research question, therefore, is whether these models are applicable to older adults.

4 Factors Influencing Goal-Directed Exploration

This section discusses three factors that may lead to significant differences not captured in current models.

4.1 Working Memory

Working memory is the mental process by which information is temporarily stored and manipulated in the performance of complex cognitive tasks such as language understanding, learning and reasoning. Many different types of information can be held in working memory, including visual, verbal, and emotional information [28].

Measures of working memory correlate well with performance on many tasks, especially those that involve both memory and processing. Working memory capacity shows a decline with age, and is considered to be a key determinant of age-related differences in performance on cognitive tasks [29], [30], [31]. Age differences in performance on memory tasks are greater for tasks involving more executive processing [32], [33]. Reuter-Lorenz and Sylvester [34] suggest that this may be due to the use of executive processing resources to compensate for declines in memory ability. It is well known that recall is a more difficult memory task than recognition. Craik and McDowd [35] showed that increased age amplifies the cost of memory recall. Older adults may also be less able to suppress interfering memories [36], [37] during encoding and retrieval of information.

Baddeley and Hitch's influential model of working memory [38] posits three primary subcomponents of working memory: an 'attentional-controlling system' (or 'central executive'), a 'phonological loop' that stores and rehearses verbal and other auditory information, and a 'visuo-spatial scratch pad' that manipulates visual images. More recently, an 'episodic buffer' component has been proposed, serving the purpose of integrating working memory information with that in long-term memory [39].

Working memory has a role in performance that goes beyond age-related differences. Impairments in aspects of working memory have been found with a number of disabilities, including schizophrenia [40], ADHD [41], and learning disabilities [42]. This impacts performance in many tasks. Naumann et al [43] provided strategy training to individuals in how to learn from hypertext, and found that the effectiveness of this training depended on the working memory resources of the individuals. For learners with poorer working memory, the strategy training actually hindered their performance. Furthermore, modern computing contexts often tax working memory with frequent interruptions and multi-tasking demands.

4.2 Prior Knowledge

Prior knowledge has been found to influence goal-directed exploration. Older adults, having greater life experience on which to draw, may outperform younger adults in ill-defined Web-based tasks that rely on background knowledge of the topic [44].

The effect of knowledge on exploration is core to information foraging. Scent depends on the perceived relationship between what is on the screen and the users goal. To date, information foraging models have treated scent as a lexical relationship. It is calculated relative to lexical relationships in a pre-existing corpus. One can think of scent calculations as using a corpus of documents to ‘stand-in’ for the users knowledge.

There are likely to be generational differences in background knowledge. For example, different age groups will have learned different topics at school, different age groups will tend to have read different books and be exposed to different media. The effects of background knowledge are readily apparent in different English speaking cultures. For example, when asked to find ‘vacuum cleaners’, people who have grown-up in the UK will likely follow a link that says ‘Hoovers’. Use of the term ‘Hoover’ to refer to a vacuum cleaner is common in the UK, so will be background knowledge. Among English language speakers who have grown-up in the US, however, younger adults are very unlikely to click such a link, as it would not appear to be related to their goal. In information foraging terms, for someone who has grown-up in the US, ‘Hoover’ would not have high scent when the search goal was ‘vacuum cleaner’. These differences in background knowledge may be sufficient to change users’ exploration behavior, and background knowledge may be similar enough within a generation to see generational differences in exploration behavior.

4.3 Information-Seeking Strategies

In an information foraging task, participants must maintain many items in memory: the current goal, the paths already explored, and other promising unexplored paths, in addition to making judgments of the information scent of each option. As a result, performance in such tasks may be quite sensitive to working memory capacity. It may even be the case that people with lower working memory capacity employ very different strategies, in order to compensate.

In a loosely constrained information-seeking task, Fairweather [45] observed that while there were no differences in task success between an older and younger group, there were significant differences in how the task was approached, and strong age-related tendencies to follow particular paths and visit particular zones. Older adults made more use of guided small steps, performed more fruitless searches, and left the original site more often. Fairweather concluded that the observed performance differences could not be attributed to taking the same steps in a less efficient way – fundamentally different approaches were being used.

In a study of adaptive foraging behavior in a virtual landscape, both younger and older adults adjusted the parameters of their foraging strategy in response to task characteristics, but the performance of the older group was poorer, even when an optimal strategy was explicitly taught [46].

Hanson also observed strategy differences between older and younger individuals performing Web search tasks, but no significant differences in task success [47]. Paxton et al [48] report MRI-based results that also suggest a strategy change in older adults in a task that stressed maintenance of goal-relevant information. They hypothesize that problems with goal maintenance lead to this shift.

Cognitive models of foraging strategies, when compared with human data, can be a useful way to explore possible alternative strategies in different user groups.

5 Research Directions

In light of the discussion above, our research is exploring the following questions: How do the strategies of younger and older adults compare on information foraging tasks? What cognitive skills, including working memory, correlate with task performance and strategy use? How well can information foraging models predict human data? What is the influence of information scent algorithms and corpora?

5.1 Collecting Human Data from a Broader Population

Our approach is to gather very detailed data from older and younger adults performing a goal-directed search task on the Web, to augment existing knowledge of human information foraging. Our data includes keyboard, mouse, and eye movement information.

Our initial experiments are utilizing an information space derived from a popular online auction site in the UK. Items in this space are organized in a three-level category hierarchy with the top level including 27 categories such as “Antiques”, “Art”, “Baby”, “Jewellery & Watches”, “Musical Instruments”, and “Photography”. Research participants are being asked to find the proper third-level category for a named item such as “Watch batteries”. In this case the correct path would be “Jewellery & Watches”, “Watches”, “Watch Batteries”. Each of the second-level and third-level screens has a “Go Back” button making it easy to navigate back up the hierarchy. In addition, each screen has a reminder string of the form “Looking for x” to remind participants of their goal. By examining the eye-movement data we will be able to see what is considered, how long each item is considered, and whether the reminder string is utilized.

5.2 Modeling Between-Group Differences in Information Foraging

ACT-R models offer predictions of how the motor actions, eye movements, and cognition are interweaved in the performance of a task. We plan to develop models that represent theories of how users are performing the task. Different corpora to represent different knowledge bases are another possible avenue of exploration.

Comparing different models with human data will test these theories, leading to a deeper understanding of age-related differences in information foraging.

The cognitive model currently underlying CogTool-Explorer has been successful in predicting user behavior in Blackmon's dictionary search tasks [19]. Although it is an ACT-R model, the goal, and the best link seen so far, are stored in ACT-R's goal buffer, where they are not subject to decay. Differences in working memory abilities cannot be represented in this model. If issues of forgetting the goal term, or the best link seen so far arise in the data, more sophisticated models will be required to capture these effects.

ACT-R's working memory mechanism will provide a basis for models that account for forgetting. The ACT-R cognitive architecture implements a model of working memory, including a visual buffer and an auditory buffer. The attentional-controlling system is implemented as a fixed amount of memory activation that is spread across memory items. Each memory item has a level of activation based on the time since it was created or accessed, and connections to other active elements. Those items with an activation level above a threshold are active 'working memory' chunks. Anderson et al [49] describe experiments supporting this 'source activation' model, and ACT-R models can account for many effects observed in psychological experiments [50]. Huss and Byrne [51] further proposed an ACT-R based model of an articulatory loop, in which an individual repeatedly sub vocally verbalizes an item in order to rehearse it and maintain its activation in working memory. Their model was able to reproduce the effects of list length and stimulus length on a list recall task. Sub vocal (or even vocal) articulation is a commonly used memory strategy, and may be important for accurate modeling of tasks involving memory.

The ultimate goal of our research work is to derive and validate models capable of being embedded in CogTool-Explorer and used by designers to predict the behavior of a broad range of users exploring unfamiliar Web sites or user interfaces. Using data from older and younger user groups, the applicability of current models can be examined, and new models developed. We have discussed working memory, prior knowledge, and information-seeking strategies. These three factors, when reflected in models, may help to account for between-group differences in exploratory behavior.

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References

1. Card, S.K., Moran, T.P., Newell, A.: The Psychology of Human-Computer Interaction. Lawrence Erlbaum Associates, Hillsdale (1983)
2. Gray, W.D., John, B.E., Atwood, M.E.: Project Ernestine: Validating a GOMS Analysis for Predicting and Explaining Real-World Task Performance. Human-Computer Interaction 8(3), 237–309 (1993)
3. Callander, M., Zorman, L.: Usability on Patrol. In: CHI 2007 Extended Abstracts on Human Factors in Computing Systems, San Jose, CA, USA, April 28 - May 03, pp. 1709–1714. ACM, New York (2007)

4. John, B.E., Kieras, D.E.: Using GOMS for User Interface Design and Evaluation: Which Technique? ACM Transactions on Computer-Human Interaction 3(4), 287–319 (1996)
5. Luo, L., John, B.E.: Predicting Task Execution Time on Handheld Devices Using the Keystroke-Level Model. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2005), Portland, Oregon, April 2-7. ACM, New York (2005)
6. Knight, A., Pyrzak, G., Green, C.: When Two Methods Are Better Than One: Combining User Study with Cognitive Modeling. In: CHI 2007 Extended Abstracts on Human Factors in Computing Systems, San Jose, CA, USA, April 28 - May 03, pp. 1783–1788. ACM, New York (2007)
7. John, B.E., Prevas, K., Salvucci, D.D., Koedinger, K.: Predictive Human Performance Modeling Made Easy. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2004), pp. 455–462. ACM, New York (2004)
8. Daily, L., Lovett, M., Reder, L.: Modeling Individual Differences in Working Memory Performance: A Source Activation Account. Cognitive Science 25, 315–353 (2001)
9. Rehling, J., Lovett, M., Lebiere, C., Reder, L., Demiral, B.: Modeling Complex Tasks: An Individual Difference Approach. In: Proceedings of the 26th Annual Conference of the Cognitive Science Society, Chicago, IL, August 4-7, pp. 1137–1142 (2004)
10. Jastrzembski, T.S., Charness, N.: The Model Human Processor and the Older Adult: Validation in a Mobile Phone Task. Journal of Experimental Psychology: Applied 13, 224–248 (2007)
11. Jastrzembski, T.S., Myers, C., Charness, N.: A Principled Account of the Older Adult in ACT-R: Age Specific Model Human Processor Extensions in a Mobile Phone Task. In: Proceedings of the Human Factors and Ergonomics Society 54th Annual Meeting, San Francisco, CA, September 27-October 1 (2010)
12. John, B.E., Jastrzembski, T.S.: Exploration of Costs and Benefits of Predictive Human Performance Modeling for Design. In: Salvucci, D.D., Gunzelmann, G. (eds.) Proceedings of the 10th International Conference on Cognitive Modeling, Philadelphia, PA, pp. 115–120 (2010)
13. Pirolli, P., Card, S.: Information Foraging in Information Access Environments. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 1995), pp. 51–58. ACM Press, New York (1995)
14. Pirolli, P.: Computational Models of Information Scent-Following in a Very Large Browsable Text Collection. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 1997), pp. 3–10. ACM Press, New York (1997)
15. Pirolli, P.: Information Foraging Theory: Adaptive Interaction with Information. Oxford University Press, New York (2007)
16. Lawrance, J., Bellamy, R., Burnett, M., Rector, K.: Using Information Scent to Model the Dynamic Foraging Behavior of Programmers in Maintenance Tasks. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2008), pp. 1323–1332. ACM Press, New York (2008)
17. Lawrance, J., Burnett, M., Bellamy, R., Bogart, C., Swart, C.: Reactive Information Foraging for Evolving Goals. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2010), pp. 25–34. ACM, New York (2010)
18. Anderson, J.R.: The Adaptive Character Of Thought. Erlbaum, Hillsdale (1990)
19. Blackmon, M., Kitajama, M., Polson, P.: 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 (CHI 2005), pp. 31–40. ACM Press, New York (2005)

20. Chi, E., Rosien, A., Supattanasiri, G., Williams, A., Royer, C., Chow, C., Robles, E., Dalal, B., Chen, J., Cousins, S.: The Bloodhound Project: Automating Discovery of Web Usability Issues Using the InfoScent™ Simulator. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2003), pp. 505–512. ACM Press, New York (2003)
21. Teo, L., John, B.E.: Towards a Tool for Predicting Goal-Directed Exploratory Behavior. In: Proceedings of the Human Factors and Ergonomics Society 52nd Annual Meeting, pp. 950–954 (2008)
22. Anderson, J., Lebiere, C.: The Atomic Components of Thought. Erlbaum, USA (1998)
23. Fu, W., Pirolli, P.: SNIF-ACT: A Cognitive Model of User Navigation on the World Wide Web. Human-Computer Interaction 22(4), A355–A412 (2007)
24. Halverson, T., Hornoff, A.: A Minimal Model for Predicting Visual Search in Human Computer Interaction. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2007), pp. 431–434. ACM Press, New York (2007)
25. Turney, P.D.: Mining the Web for Synonyms: PMI-IR Versus LSA on TOEFL. In: Proceedings of the Twelfth European Conference on Machine Learning, Freiburg, Germany, pp. 491–502 (2001)
26. Stone, B., Dennis, S., Kwantes, P.J.: A Systematic Comparison of Semantic Models on Human Similarity Rating Data: The Effectiveness of Subspacing. In: The Proceedings of the Thirtieth Conference of the Cognitive Science Society (2008)
27. Kitajima, M., Blackmon, M.H., Polson, P.G.: Cognitive Architecture for Website Design and Usability Evaluation: Comprehension and Information Scent in Performing by Exploration. In: Proceedings of the HCI International Conference (2005)
28. Mikels, J., Larkin, G., Reuter-Lorenz, P.: Divergent Trajectories in the Aging Mind: Changes in Working Memory for Affective Versus Visual Information with Age. Psychology and Aging, APA 20(4), 542–553 (2005)
29. Salthouse, T.A.: Differential Age-Related Influences on Memory for Verbal-Symbolic Information and Visual-Spatial Information. Journal of Gerontology 50B, 193–201 (1995)
30. Park, D.C., Lautenschlager, G., Hedden, T., Davidson, N.S., Smith, A.D., Smith, P.K.: Models of Visuospatial and Verbal Memory Across the Adult Life Span. Psychology and Aging 17, 299–320 (2002)
31. Brown, S.C., Park, D.C.: Theoretical Models of Cognitive Aging and Implications for Translational Research in Medicine. The Gerontologist 43(suppl. 1), 57–67 (2003)
32. Dobbs, A.R., Rule, B.G.: Adult Age Differences in Working Memory. Psychology and Aging 4, 500–503 (1989)
33. Salthouse, T.A., Babcock, R.L.: Decomposing Adult Age Differences in Working Memory. Developmental Psychology 27, 763–776 (1991)
34. Reuter-Lorenz, P., Sylvester, C.: The Cognitive Neuroscience of Working Memory and Aging. In: Cabeza, R., Nyberg, L., Park, D. (eds.) Cognitive Neuroscience of Aging: Linking Cognitive and Cerebral Aging, pp. 186–217. Oxford University Press, Oxford (2005)
35. Craik, F., McDowd, J.: Age Differences in Recall and Recognition. Journal of Experimental Psychology: Learning, Memory and Cognition 13(3), 57–67 (1987)
36. May, C.P., Hasher, L., Kane, M.J.: The Role of Interference in Memory Span. Memory and Cognition 27, 759–767 (1999)
37. Lustig, C., May, C.P., Hasher, L.: Working Memory Span and the Role of Proactive Interference. Journal of Experimental Psychology 130, 19–207 (2001)
38. Baddeley, A.D., Hitch, G.J.: Working memory. In: Bower, G.A. (ed.) Recent Advances in Learning and Motivation, pp. 47–89. Academic Press, London (1974)

39. Baddeley, A.: The Psychology of Memory. In: Baddeley, A., Kopelman, M., Wilson, B. (eds.) The Essential Handbook of Memory Disorders for Clinicians, ch.1. John Wiley & Sons, Chichester (2004)
40. Silver, H., Feldman, P., Bilker, W., Gur, R.C.: Working Memory Deficit as a Core Neuropsychological Dysfunction in Schizophrenia. American Journal of Psychiatry 160, 1809–1816 (2003)
41. Marusiak, C., Janzen, H.: Assessing the Working Memory Abilities of ADHD Children Using the Stanford-Binet Intelligence Scales. Canadian Journal of School Psychology 20(1-2), 84–97 (2005)
42. Swanson, H.: Individual Differences in Working Memory: A Model Testing and Subgroup Analysis of Learning-Disabled and Skilled Readers. Intelligence 17(3), 285–332 (1993)
43. Naumann, J., Richter, T., Christmann, U., Groeben, N.: Working Memory Capacity and Reading Skill Moderate the Effectiveness of Strategy Training in Learning from Hypertext. Learning and Individual Differences 18(2), 197–213 (2008)
44. Chin, J., Fu, W., Kannampallil, T.: Adaptive Information Search: Age-Dependent Interactions Between Cognitive Profiles and Strategies. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2009), Boston, MA, USA, April 04–09, pp. 1683–1692. ACM, New York (2009)
45. Fairweather, P.: How Younger and Older Adults Differ in Their Approach to Problem Solving on a Complex Website. In: Proceedings of 10th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS 2008). ACM Press, New York (2008)
46. Mata, R., Wilke, A., Czienskowski, U.: Cognitive Aging and Foraging Behavior. J. Gerontol. B Psychol. Sci. Soc. Sci. 64B(4), 474–481 (2009)
47. Hanson, V.: Influencing Technology Adoption by Older Adults. Interacting with Computers 22, 502–509 (2010)
48. Paxton, J., Barch, D., Racine, C., Braver, T.: Cognitive Control, Goal Maintenance, and Prefrontal Function in Healthy Aging. Cerebral Cortex 18(5), 1010–1028 (2008)
49. Anderson, J., Reder, L., Lebiere, C.: Working Memory: Activation Limitations on Retrieval. Cognitive Psychology 30, 221–256 (1996)
50. Anderson, J., Bothell, D., Lebiere, C., Matessa, M.: An Integrated Theory of List Memory. Journal of Memory and Language 38, 341–380 (1998)
51. Huss, D., Byrne, M.: An ACT-R/PM Model of the Articulatory Loop. In: Detje, F., Doerner, D., Schaub, H. (eds.) Proceedings of the Fifth International Conference on Cognitive Modeling, pp. 135–140. Universitats-Verlag Bamberg, Germany (2003)