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An analysis of age, technology usage, and cognitive characteristics within information retrieval tasks

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This work presents two studies that aim to discover whether age can be used as a suitable metric for distinguishing in performance between individuals, or if other factors can provide a greater insight. Information retrieval tasks are used to test the performance of these factors. First a study is introduced that examines the effect that fluid intelligence and Internet usage has on individuals. Second, a larger study is reported on that examines a collection of Internet and cognitive factors in order to determine to what extent each of these metrics can account for disorientation in users.

This work adds to growing evidence showing that age is not a suitable metric to distinguish between individuals within the field of human computer interaction. It shows that factors such as previous Internet experience and fluid based cognitive abilities can be used to gain a better insight into users' reported browsing experience during information retrieval tasks.

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1. INTRODUCTION

The Internet is a ubiquitous technology that is used to find information, communicate with others, and gain access to online services. Recent Ofcom statistics [2014] state that 79% of UK homes had access to the Internet in 2012. This is a large increase from only six years previously where 54% of homes reported having similar access. In addition to this, the prevalence of Internet usage by older adults is also increasing year on year. This increase in Internet uptake is likely to continue as the

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technology allowing this reduces in price, and methods such as smartphones and tablets are seeing increased adoption rates [Ofcom 2013, p.38].

The reliance on the Internet for individuals to obtain information now means that the design of digital services must take into consideration a wide range of ages and abilities. This concept is not new and a large corpus of design guidelines exists that focus on making websites more 'senior friendly' [Hodes and Lindberg]. These guidelines mainly focus on the physical changes that are associated with aging (e.g. degradation in eyesight and fine motor skills). In turn, this can create websites that stereotypically have larger text and bigger buttons. These sites can also contain less information on a page-to-page basis and increased accessibility options such as text resizing and contrast adjustment. While some of these factors may be beneficial, these changes are recommended to create a 'senior-friendly' experience.

In addition to the physical changes that accompany aging, there is a large body of evidence showing that cognitive changes also occur (e.g. [Horn and Cattell 1967]). These cognitive changes can affect many abilities throughout an individual's lifespan. Fluid intelligence (described as the problem solving abilities of an individual) increases until early adulthood before it begins to decline. In contrast, crystallized intelligence, (described as the body of knowledge that individuals acquire over their lifetime) increases until late adulthood before tailing off [Horn and Donaldson 1980].

Supporting the evidence of cognitive decline that accompanies aging, there is now a growing interest in the role that cognitive abilities have in relation to the design of digital services [Rogers and Fisk 2010]. This work, presenting two user studies, focuses on the role of fluid cognitive abilities and their impact on older adults' performance in information retrieval task. Experiment 2 in this work was previously published by Crabb and Hanson [2014]. In this version, the research context is expanded upon and previously unpublished work (Experiment 1) is presented.

2. RELATED WORK

When categorising users it is important to consider similarities and differences that exist in order to distinguish between individuals. There are many different measurement characteristics that can be used to accomplish this. In particular, age and cognitive abilities are of interest in this work. This section introduces and examines previous work investigating these metrics.

2.1 Using Age to Distinguish Between Users

It is common in research to distinguish between individuals by using age as a metric. This is especially prevalent when examining technology usage information for a population. In this context, assumptions can be made surrounding population groups and their patterns of technology adoption. For example, Ofcom regularly produces reports on technology usage information for the United Kingdom. Their recent Media Use and Literacy Report [2013] notes that 50% of older adults age 65-74 had access to the Internet in their home, with 25% of older adults aged 75+ having similar access. Older adults are a group that has seen substantial growth in technology usage over the last decade, and are also becoming more confident in its usage.

The stereotypical view of older adults' not understanding technology is inaccurate. Older adults use a wide variety of technology devices, with a large number of these appearing in their homes. Additionally, older adults consider that the benefit of new technology outweigh the cost associated with its uptake, believing that the convenience and useful features attached to some technological devices are worth the additional cost [Mitzner et al. 2010].

However, differences exist in technology usage between older and younger adults. Older adults have been shown to take fewer risks to find information, even if this would result in taking more time than by using other methods. For example, Fairweather [2008] reports that older adults are more likely than younger adults to visit pages on a website that would slowly guide them through a search as opposed to carrying out a more random search on a website. Additionally, findings from the CREATE center [Czaja et al. 2006] discuss that while older adults recruited in their work are highly educated, significant age based differences in use of the Web exist. It is also discussed how this low technology uptake by older adults is likely to result in those not using technology to "more likely to become more disenfranchised and disadvantaged" [Czaja et al. 2006, p.346]. Two of the main barriers to computer usage for older adults are low-self efficacy and high anxiety attached to computer usage. Older adults that reported computer usage before retirement have been described as using computers to be a negative experience [Aula 2005]. A possible reason for this negative experience stems from developers blaming users for mistakes made rather than bad system design. This in turn may also decrease individuals' willingness to pick up new technology in the future.

These differing feelings of confidence in older adults are also present in academic literature. Low levels of technology confidence in older adults may influence the way in which they approach computer based tasks, with users not making the required effort as they believe from the outset that they will fail [Marquié et al. 2002]. Older adults that use computers to search for information believe that their ability to do this is significantly lower than reality [Aula and Nordhausen 2005]. It has been found that older adults show more anxiety towards computers than middle aged and younger adults and also show less interest in technologies such as the Internet. Subsequently, their experience in using these sorts of technologies is also lower [Czaja et al. 2006].

One of the main barriers to technology update by older adults, could well be down to a lack in training into how technology works. For example, it has been found that older adults are less likely than younger adults to use ATM machines, yet report that they would be willing to do so if they received training [Rogers et al. 1996]. Hickman, Rogers, and Fisk [2007] provide guidance on training methods that can be used to aid older adults in learning new technological skills, showing a one-size-fits-all approach does not work in regards to training and that attention must be paid to the tasks being used in order to facilitate technology uptake.

A possible solution to solving older adults' anxiety in using technology would be to better educate the younger generation so that they can use technology in later life. However, the problems faced by today's older adults regarding technology use may be replicated in future generations. This can be related to a combination of changes in technology, and also age related changes that are attached to individuals [Hanson 2011].

Marchionini and Shneiderman [1988] discuss different abilities that are essential in online browsing and the effectiveness of a user in completing an information retrieval task. This is split down into search setting, the task being searched on, the search system, and the user doing the search. By acknowledging that 'each user is unique' and separating their ability down into frequency of use, complexity of application, and general computer experience, Marchionini & Shceiderman believe that it is possible to determine how quickly and accurately users will develop mental models for a system and also how effectively they can apply these models. The models created are therefore based on a set of individual user characteristics and not the number of years since birth.

As suggested by Pak, Price, and Thatcher [2009]; much work is necessary to translate the knowledge of age difference into design recommendation. The concept of age being used to distinguish between users requires further analysis in order to examine its suitability. Previous examination into high performing older adults showed that their task performance ability was comparable to that of younger adults [Czaja et al. 2010]. Older adults aged 50 are unwillingly placed within the same technological group as those aged 80 and research involving older adults should "*take into account the full continuum of experience and abilities of older users*" [Hanson 2009].

2.2 Cognitive Characteristics to Compare Users

Another method used to compare users is examining their cognitive ability. Modern intelligence testing methods commonly use a battery of tests to examine many different aspects of an individual's intelligence. This is needed in order to fully examine all parts of individuals' abilities. "*The abilities measured by a speed test with language and mathematics are not identical with, or even very similar to, those measured by a test with picture*" [Thorndike 1920].

While cognitive abilities may have an impact in the performance of older adults when carrying out Internet based tasks, it has also been found to influence the uptake of Internet based activities. It has been suggested that individuals with higher cognitive levels are likely to use the Internet more, adopt the Internet earlier, and participate in a wider variety of web-based tasks (i.e. Internet use and e-mail) [Freese, Rivas and Hargittai 2006]

In modern testing, cognitive abilities are measured using a variety of methods with these mostly producing a score as an end result. These scores can then be used as a measurement of individuals' abilities. However, there are many factors that can influence individuals' scoring, apart from their cognitive abilities. These include aspects such as environmental development, cultural closeness (e.g. language based tests), user interest, and also user fatigue [Cattell et al. 1941]. Cognitive testing should therefore be used in a manner that highlights individuals' general ability while keeping all other variations to a minimum.

One area of cognition that has shown potential in HCI work surrounds the principle of fluid mental abilities [Dillon and Watson 1996]. This theory is based on initial work that examined the splitting of cognitive functions into two separate areas; fluid and crystallized intelligence [Cattell 1963]. Fluid intelligence is described as the ability to adapt to a particular situation because of an individual's problem solving abilities. Crystallized intelligence is described as adaption based on previous knowledge of a particular domain [Horn and Cattell 1966]. Both fluid and crystallized abilities can also be categorized as part of the CHC (Cattell-Horn-Carroll) model of human intelligence [McGrew 2009]. This splits human intelligence into nine separate factors, with these then being split into further sub-factors [Flanagan, Genshaft, & Harrison, 1997].

The process of aging results in many changes to individuals' cognitive abilities. Fluid abilities tend to diminish as from early adulthood, but crystallized abilities increase over the lifespan [Horn and Cattell 1967]. It is important to note that these changes do not occur at the same time for every individual and that generalisations such as 'early adulthood' must be used. Changes in cognitive abilities can have a profound effect on how individuals can understand new technologies and successfully carry out tasks. Fluid abilities have been shown to be important in carrying out computer based tasks. The four fluid based factors examined in this work are:

- Fluid Intelligence – *Inductive Reasoning*
- Short Term Memory – *Memory Span and Working Memory*
- Long Term Storage and Retrieval – *Meaningful Memory*
- Processing Speed – *Perceptual Speed*

2.2.1 Fluid Intelligence

Fluid Intelligence is a measure of individuals' ability to use mental operations to complete a task. This mainly involves problem-solving abilities with individuals relying on discerning relationships among patterns, extrapolating information, and the formation and recognition of concepts. This work focuses on a particular aspect of fluid intelligence: inductive reasoning. Inductive reasoning is the ability of an individual to discover the underlying rules and concepts that apply to a problem set.

One test associated with determining the indicative reasoning of an individual is the Letter Sets Test [French, Estrom & Price 1963]. This has been regularly used in a number of HCI studies. For example, Trewin et al. [2012] use this to differentiate between high and low fluid intelligence levels within older adults, using this as a step in creating predictive models for user search behaviour that take cognitive factors into consideration. Chin et. al [2009] used the Letter Sets Test, combining it with other cognitive tests to create a generic 'cognition' score to analyse the performance between older and younger adults when looking at information online.

Users with high and low scorings of fluid intelligence have previously been examined in relation to their use of online menu systems in eye-tracking studies. It has been found that although high and low fluid intelligence users would select the same amount of links before completing a task, users with low fluid intelligence would be more likely to re-select items that they had previously visited. It has also been reported that users with low levels of fluid intelligence would rely more on mouse movement prior to clicking, suggesting that it is being used as a marker to aid their movement around a search space [Trewin et al. 2012].

2.2.2 Short Term Memory

Short-term memory is the ability of individuals' to hold and use information within a few seconds of acquiring it. An example of a short-term memory application would be the ability to remember a telephone number for a long enough period to dial it. This work focuses on two sub-abilities of short-term memory, memory span and working memory. Memory span is the ability of an individual to immediately recall temporarily ordered objects after being presented with them for a short time. Working memory is similar to memory span in that the recollection of information is required after a short time, but with the addition of a cognitive operation applied to the information, for example – repeating a set of given numbers in reverse order.

When examining the design of information search interfaces for older and younger adults, short-term memory has been shown to influence the efficiency between groups when searching for information. Pak and Price [2008] established that short-term memory can be used as a predictor of performance but this is heavily based on the structure of the data being presented.

2.2.3 Long Term Storage and Retrieval

Long term storage and retrieval is described by Horn [1991] as the storage and retrieval of information that is obtained '*minutes, hours, weeks, and years before*'. Again, it is important to note the difference between long term memory and crystallized intelligence: crystallized intelligence represents an indication in *what* is being stored, long-term storage and retrieval is a measure of the *efficiency* with which things are stored [Flanagan et al. 2007]. This work uses a single narrow ability associated with long-term memory - meaningful memory. Meaningful memory can be described as the ability of an individual to recall a set of items when there is a meaningful relationship present between item sets.

Long-term memory has been used to examine the relationship between users' performance within information retrieval tasks. It has been shown that users with high levels of long-term memory navigate through systems less efficiently than those with low long-term memory. This is not the direction that results would be expected to conform with, however statistical significance occurs nonetheless [Westerman et al. 1995]. It could be possible that the reason for this surrounds an additional factor that is affecting the overall outcome as this result seems very unintuitive.

2.2.4 Processing Speed

Processing Speed is described as an individual's 'mental quickness' and requires very little complex thinking. Horn [1991] describes processing speed tasks as things that "*almost all people would get right if the task were not … under time pressure"*. This work uses a single narrow ability associated with processing speed – perceptual speed. This is a measure of an individual's ability to search and compare visual symbols or patterns in rapid succession.

In this work, processing speed is determined through the Number Comparison test [French, Estrom & Price 1963]. Although this test has not been shown to correlate significantly to the speed of a person's search (Allen [1994] reports r = .08) it has been shown to correlate with user learning and recall of data. Allen has also shown that users with high levels of processing speed can take advantage of small adjustments in the user interface. For example, Allen [1994] reported that changing a system in an information retrieval task to first display subject information instead of author information significantly increased users' performance. Allen [1992] also shows that the Number Comparison test can be used as an indicator of search quality and that high scores from this test also aid in 'browse searching' when attempting to find information. The number comparison test has also been used as part of a composite scoring of individuals' fluid intelligence. Using this scoring method, the test has been used in order to examine performance within customer service based tasks [Nair, Czaja, & Sharit, 2007], and also in the training of older adults in e-health websites [Czaja et al., 2013].

Additionally, Chin, Fu & Kannampallil [2009] include processing speed within a study examining information search, focusing on the strategies used by older and younger adults when answering ill and well defined questions. It was found that participants with high cognition and health literacy scoring performed better than their counterparts when completing well-defined tasks. It was then suggested that older adults compensated for their lower cognitive abilities by spending longer analysing the contents of a web page in order to better understand the information.

2.3 Previous Technology Usage

A common method used to gather information on users is examining their previous technology usage. This can take many forms with the most prevalent being self-reported information. Possible implementations involve using questionnaires to allow participants to report on aspects relating to technology usage, experience and comfort.

It is important to measure both the amount of experience that users have in using technology, and also their expertise, as although these items may be correlated, they are both clearly defined separate factors. In order to better understand web experience, more focus must be placed on qualitative web experience, and examining how users learn web skills as opposed to the amount of time spent doing so [Chadwick-Dias, Tedesco, & Tullis, 2004]. The Internet Usage and Confidence Questionnaires used in this work are adapted from questionnaires used by the CREATE Project. Adaptations were made to the questionnaires to make them more suitable for a UK demographic [L. Gibson, personal communication, 2013]. The Internet Usage questionnaire is loosely based on the Internet Questionnaire used in the CREATE battery of testing [Czaja, Charness, Dijkstra, et al., 2006].

2.4 User Disorientation and Effective Search Strategies

Information search is a complex cognitive activity [Dinet, Chevalier & Tricot 2012]. Literature regarding disorientation in web based systems looks largely at the systems themselves rather than its users [Botafogo, Rivlin, & Ben Shneiderman, 1992; Rodríguez, Gayo, & Lovelle, 2001; Zhang & Greenwood, 2004]. While it is easier for a developer to change a website rather than to change the way a user behaves, by examining users' cognitive characteristics a greater understanding of the reasoning behind why disorientation occurs can happen. Shih, Huang, Hsu and Chen [2012] examine this within younger adults using data mining techniques to uncover patterns. Additionally, age related differences in searching for information online can be (partly) explained by the age related decline in cognitive flexibility [Dommes, Chevalier & Lia 2011]. When examining the role of older adult cognitive ability, Pak et al. [2008] find that spatial ability has an influence on older adults performance in tasks and recommends that the design of future technologies should examine methods of reducing the load on this factor (e.g. in menu systems). It has also been shown that when examining user flow in web navigation, task performance is majorly affected by disorientation [van Schaik & Ling, 2012]. It is also possible to examine both the technological and cognitive factors to quantify online disorientation. This can be done though analysing the structure of websites and also participants' mental models of websites, examining how this can relate to feelings of disorientation [Otter & Johnson, 2000].

Users can use a variety of strategies when searching for information on the Internet. It has been suggested that these strategies used in information searching have commonalities in the triggers used to prompt further searching and also in steps used to analyze search results [O'Day and Jeffries 1993]. Supporting this viewpoint, Teevan et. al [2004] report that participants used their own contextual knowledge of a situation to help within an *orienteering strategy* that aided in searching or information. It has also been suggested that older adults would benefit if search systems were organised using a *tag structure* so that demand can be placed on their vocabulary (i.e. crystallized) knowledge [Pak and Price 2008]

Website navigation can also be examined in order to learn more about the overall usability of an individual site. Blackmon, Kitajima and Polson [2005] suggest doing this through using an automated 'cognitive walkthrough' method. This involves examining the links, headings, and subject matter of a website in order to estimate in number of clicks needed to find information on a single website. Vaucher and Sahraoui [2010] take a similar approach and suggest that by examining how easy an individual page is to navigate and by looking at how easy the website as a whole is to navigate a better understanding of site usability can be achieved.

3. INTERNET USAGE & INDUCTIVE REASONING IN RELATION TO USER PERFORMANCE

Previous literature has examined the overall role that cognitive abilities have when using technology. The purpose of this experiment is to further develop an understanding in this area, focusing on the role that inductive reasoning and Internet usage have on user performance in information retrieval tasks.

An initial experiment was performed in order to develop an understanding into the role that cognitive abilities have when users are searching for information online. This experiment examines inductive reasoning, Internet usage, and age as metrics that may distinguish between users' browsing performance. A quantitative approach is used to examine whether these factors can be used to differentiate between user performance when searching for information online.

3.1 Experimental Design

Participant age group, Internet usage, and inductive reasoning were used as independent variables. Search engine usage efficiency and task speed were used as dependent measures.

3.1.1 Participants

Eighteen participants were recruited for this experiment. This consisted of 12 older adults (*M* = 67.17, *SD* = 5.36 Range = 65-81) and six younger adults (*M* = 19.83, *SD* = 0.68, Range = 23-25). Older adults were recruited from a user pool of local participants, all of which have agreed to take part in HCI research [Dee and Hanson 2014]. These participants were contacted by a user pool coordinator through phone and e-mail and invited to take part in the experiment. Younger adults were recruited through e-mail and university message boards. All participants clarified in pre-screening that they had not taken part in any HCI research studies in the past 12 months.

Older adults who participated in this experiment had previously completed a number of cognitive tests and questionnaires as part of an information gathering exercise [Dee and Hanson 2014]. Users were therefore recruited based on test scorings previously obtained in the Internet usage and inductive reasoning tests. This allowed for user groups to be created with participants pre-sorted into high/low inductive reasoning and high/low Internet usage groupings. A significant difference was present between high (M = 17.17, SD = 4.83) and low inductive reasoning (M = 6.0, SD = 3.35) groupings ($t(10)=4.65$, $p < .001$) and also between high (M = 3.64, SD = .62) and low Internet usage (M = 1.62, SD = .42) participant groups ($t(10) = 6.55$, $p < .001$.).

The six younger adults were all university undergraduates studying degrees in Law, Medicine or Teaching. All had previously stated that they use search engines on a regular basis and this was confirmed in their Internet Usage questionnaire scorings (M = 3.68, SD = .496). Younger adults showed a slightly higher Internet Usage score than high Internet usage older adults (M = 3.64, SD = .62) but this was not at a significant level ($t(10) = .781$, $p > .25$).

3.1.2 Dependant Measures

Two dependant measures were used in this work; search engine usage efficiency, and task speed. These measures, detailed below, were used to measure the performance of participants and are used objectively to compare characteristics between participants. It is worth acknowledging that these do not directly measure the quality of participants operations and instead measures their efficiency in creating and manipulating search query, and the overall speed at which a user navigates through a website. At no point should it be assumed that high or low values of these metrics are indicative to the quality of the overall experience felt by users in this session.

Search Engine Usage Efficiency consisted of two aspects; the mean number of words per search string, and the mean time on a search engine (Google) per search.

- *Mean Time on Search Engine (Google) per Search String Entered* was used as a measure of how quickly participants could go from entering a search string to selecting a search result that they believed was suitable. Users are very likely to click on the first link in the search engine when looking for information [Granka et al. 2004]. It is anticipated that users with high Internet Usage would do this more regularly and that users with low Internet Usage would spend more time reading search links before selecting a link. However, it has also been suggested that expert searchers will behave in the opposite manner, spending more time deciding on what link to select and therefore having an increased mean time for each search string entered.
- *Mean Words Per Search String* was included as a metric to measure how strict participants would be when entering search strings. While expert searchers may use advanced search strings while searching for information[1], it is anticipated that participants in this work will not attempt to use these more advanced features.

Task Speed consisted of two variables, the mean web pages visited per minute, and the mean mouse clicks per minute.

- *Mean Web Pages Visited Per Minute* was included to examine the speed in which users will navigate through websites during the experiment. It is expected that participants with higher levels of Internet Usage would visit a larger number of web pages than participants with low levels of Internet Usage. This would result in producing a higher mean number of web pages visited per minute.
- *Mean Mouse Clicks Per Minute* was included to examine if there was any difference between the results obtained between it, and the mean number of web pages visited per minute The mean mouse clicks per minute is a metric that is highly correlated to the mean web pages visited per minute; each web page visited would result in an increase in mouse clicks. However, additional mouse clicks may be registered if participants were to click on items that are not links, interact with additional elements on a page, or to repeatedly click on links while new pages are loading.

3.1.3 Materials and Equipment

Demographic Information —Demographic information including participant age, education and occupational status were collected from participants during the screening process.

Internet Usage—A questionnaire examining Internet usage [Czaja 2006b] was administered to all participants prior to taking part in the experiment and used in the screening process. This examined how often a participant completed a set of different Internet based tasks and consisted of 19 questions, measured on a 7-point scale (Everyday, Several Times a week, Several Times a month, Every few months,

[1] http://www.google.com/advanced_search

Less Often, Never). A mean score was then created for each participant based on his or her responses.

Task Question Set—Three different scenarios were created that are similar to activities that would normally be carried out online [Ofcom 2011, p.35], allowing for information to be gathered on participants information retrieval abilities and the interactions between users and the websites they visit. Tasks were split into three different categories:

- **Comparative Data:** Tasks in which the user would normally choose to make a direct comparison between two or three different sites before making a decision. In this case it included activities such as finding a hotel, where many different sites exist that can give further information on what is desired.
- **Non-Comparative Data:** Tasks in which the user would normally only check one website for a piece of information. In this case an activity such as checking local weather was used, as this is information that would not normally be looked at on more than one website. For example, finding out weather information for the duration of a holiday
- **Website Paths:** Tasks in which the participant would search for an individual subject, go deep into a website to find specific information, and then back to a search results page to select another site. This would occur multiple times and a path of visited sites would be created. For example, organising a tour of several museums in the local area.

While these categories were created as a method to frame questions throughout the study and to aid in giving a broad range of activities to participants, overlap exists in their implementation. For example, website paths may be created when looking for both comparative and non-comparative data, and the number of sites visited (to determine a comparative or non-comparative situation) may change based on the first website that is visited. Example questions from this are given in Table 1.

Table 1 - Example Questions from Task Question Set

Question Type	Question
Comparative Data	Imagine that you are going on holiday to Greece. Compare the price of three different flights that you could take.
Non-Comparative Data	Your holiday in Greece is going to be in the first 2 weeks in October, what is the weather likely to be like at this time of year?
Website Paths	You would like to visit a selection of museums while visiting Greece, what possible venues could visit on this tour?

Experimental Equipment—The experiment was carried out on an Apple laptop computer (MacBook Pro Mid-2010[2]) with the Google Chrome Browser being used. Participants were positioned in front of larger 22” Widescreen Monitor that was attached to the laptop computer and given a standard Microsoft Keyboard and Mouse to use. The researcher was positioned in front of the original laptop and used this as

[2] http://support.apple.com/kb/SP584

a 'second screen' to observe participants browsing behaviour during the study. The researcher did not interact with the computer system during the study and participants were given full control over what pages would be visited.

3.1.4 Procedure

Participants were invited to take part in a one-to-one session where they were given a set of information retrieval scenarios to carry out online. Participants were firstly given a broad description of the aim of the study, being told that it was to look at the problems that exist while searching online because of web usability issues and not the individual problems that a particular user may face. Participants were then given scenarios from the *task question set* to complete. At the beginning of each task, the browser was set to the Google home page[3].

Users continued completing these tasks until 45 minutes had elapsed. This ensured that a relatively similar amount of data was collected for each participant. This method meant that in some cases, participants did not complete all scenarios as the time taken by individuals to complete these information retrieval tasks varied greatly.

3.1.5 Analysis

The purpose of analysis is to examine differences that may be present between groups, with inductive reasoning and Internet usage being used as independent variables. The data were analysed using ANOVAs, followed by post-hoc t-tests when significance was found. Bonferonni corrections were applied to all testing.

3.2 Results

The groupings between older adult participants were made to highlight high and low dimensions of inductive reasoning and Internet usage. Separate analyses examining search engine usage efficiency and task speed were conducted.

Table 2 - Descriptive information comparing search engine usage efficiency and participant Internet usage

	Mean Time Per Search (s)	Words Per Search String (words)
	M (SD)	*M (SD)*
High Internet Usage	26.09 *(12.16)*	4.34 (.436)
Low Internet Usage	56.00 *(17.1)*	3.69 (.317)

A 2 (High / Low Internet Usage) x 2 (Mean Time Per Search / Mean Words Per Search String) MANOVA was used to examine the search engine usage efficiency between users with high and low Internet Usage. Search efficiency was previously defined as including the time spent on a search engine for each search and the number of words per search string. A significant interaction effect was found between these groups [$F(2, 12) = 6.395$, $p = .038$]. Additionally, a significant main effect was found in the time spent on search engine per search string [$F(1,12) = 12.20$, $p = .024$),

[3] http://www.google.co.uk

d = 2.02] between high and low Internet Usage groups. No significant main effect was observed in the average number of words per search string [F(1,12) = 8.843, p = .056), d = 1.71] between high and low Internet Usage participants.

These results suggest that the previous Internet usage of participants has an influence on their search engine efficiency. Participants with high Internet usage would spend less time on a search engine before selecting a link than participants with low Internet usage.

No significant difference was obtained in the average number of words per search string that high and low Internet usage participants used when trying to find information. Thus, the length of their search terms high usage participants were not were not consistent with the prolonged search selection techniques reported for younger 'expert' searchers. Given the limited number of participants in this study, lack of significance should be interpreted with caution and further explored in future research.

Table 3 - Descriptive information comparing task speed and participant Internet usage

	Mean Pages Visited Per Minute	Mean Clicks Per Minute
	M (SD)	*M (SD)*
High Internet Usage	1.65 (.465)	2.19 (.466)
Low Internet Usage	.925, (.124)	1.53 (.271)

A second MANOVA was used to examine task speed between users with high and low Internet Usage. Task speed consists of metrics surrounding the average number of pages visited per minute, and the average number of mouse clicks per minute. A significant interaction effect was found between these groups [F(2,12) = 6.329, p = .038]. Additionally, a significant main effect in the average number of pages visited per minute [F(1,12) = 13.73, p = .016, d = 2.13] between high and low Internet usage groups was observed. No significant main effect in the mean clicks per minute [F(1,12) =8.856, p = .056, d = 1.73] between high and low Internet usage groups was observed.

Combined, these results indicate that differences exist in the online behaviour of participants in this study based on their prior experience in using the Internet. Participants with high Internet usage visited more webpages than those with low Internet usage while no difference was observed in the average number of mouse clicks per minute between these two groups. This could occur for two possible reasons. Firstly, participants with high Internet usage may have lower mis-clicks (i.e. higher mouse accuracy) than those with low Internet usage and therefore visit more pages. Secondly, participants with low Internet usage may spend more time interacting with static page elements (e.g. drop down menus, tool tips, and media controls). An alternative, and more likely, explanation would be that participants with low Internet usage may spend more time reading all of the available information on a page while expert users would click rapidly through pages without reading until they had found the information that they required by skimming pages.

Two additional ANOVAs were used to examine users with high and low inductive reasoning. No significant effects were found when examining search engine usage efficiency [F(2,12) = .221, p > 1.] or task speed [F(2,12) = .253, p > 1.].

Differences were also examined between younger adults and the six older adults with a high level of Internet usage. Due to the makeup of the testing design, this group included older adults with differing levels of fluid intelligence. Similar analyses to that performed between older adult groupings were performed between older and younger adults.

Table 4 - Descriptive information comparing search engine usage efficiency with young and older adult Internet usage

	Mean Time Per Search (s)	Words Per Search String (words)
	M (SD)	*M (SD)*
Older Adult	26.09 *(12.16)*	2.75 *(.381)*
Younger Adult	11.58 *(1.99)*	2.28 *(.521)*

Similar to previous analysis, a 2 x 2 MANOVA was carried out examining the search engine usage efficiency between older and younger adults. A significant interaction effect was found between these two groups [F(2,12) = 6.931, p = .030]. However no significant main effect was found in the words per search string [F(1,12) = 3.179, p = .210, d = 1.02] between younger and older adults and also in the time on search engine (Google) [F(1,12) = 6.050, p = .068, d = 1.66] between younger older adults. Combined these results suggest that while a difference was observed in the search engine usage efficiency between older and younger adults, Bonferroni corrected results indicate that no individual aspect measured was found to contribute to this in a significant way.

	Mean Pages Visited Per Minute	Mean Clicks Per Minute
	M (SD)	*M (SD)*
Older Adult	.616 *(.216)*	.861 *(.259)*
Younger Adult	1.42 *(.335)*	1.42 *(.538)*

A second MANOVA was then performed examining task speed between older and younger adults. A significant effect was found between these groups [F(2,12) = 12.823, p = .005]. A significant difference was found in the number of pages visited per minute [F(1,12) = 24.47, p = .002 d = 2.85] between younger and older adults. No significant difference was found in the clicks per minute [F(1,12) = 5.406, p = .168 d = 1.32] between younger and older adults. However, it is interesting to note that the variance present in younger and older adults (measured by standard deviation) varied greatly.

This result is very similar to that found between older adults with high and low Internet usage in that younger adults visited more pages per minute than older adults, yet no difference could be seen between their number of average clicks per minute. This suggests that younger adults could be performing fewer mis-clicks on a page, or are using less interactive elements on pages and quickly moving between pages.

3.3 Discussion

The results from this experiment suggest that a significant factor in determining older adults' search performance relates to their previous Internet usage. Users with high levels of Internet usage spent less time searching for relevant pages on Google, visited a higher number of pages, yet used a comparable number of mouse clicks to older adults with low Internet usage. No statistical difference was found between groups of high and low fluid intelligence. However, this is likely due to the measurements that were recorded during the experiment and the fact that they are all very closely linked to computer based abilities and not a problem-solving task.

Similar to above, a significant difference was found when comparing older and younger adults. Younger adults visited more pages per minute than older adults, yet performed a comparable number of mouse clicks for minute, suggesting that they are either being more efficient and accurate in their use of the mouse, or are not using interactive elements on web pages as much as older adults. No difference was found in the average words per search term or the time spent deciding on what link to select in a search engine between older and younger adults.

3.4 Conclusions

This experiment set out to investigate if differences exist between users online search performance when examining their age, inductive reasoning, and previous Internet usage. Significant differences between older adult users' online capabilities and their reported previous Internet usage was highlighted with no statistically significant differences noticed when examining users' fluid intelligence. However, a number of limitations need to be considered. First, the small sample size must be taken into consideration. Although statistical significance was found in some cases, caution must be applied. To increase the validity of analysis, a much larger sample size is needed. Second, the current experiment only examined the effect of a single cognitive and Internet experience factor. It would be beneficial to include additional factors in order to achieve a more in depth analysis.

In a second study we therefore took a more comprehensive look into the different cognitive abilities that are used by individuals when searching for information online, and to what degree these abilities can help or hinder the experience that users have when using the Internet. More information on this would help to establish the effect that user abilities can have on the performance of an individual when searching for information online.

4. THE EFFECT OF AGE, COGNITIVE MEASURES & INTERNET ABILITY ON BROWSING EXPERIENCE

The previous experiment conducted an analysis into user factors that can be used to predict performance within an information retrieval task. It was suggested that previous Internet usage could be used as a predictor of a users' ability to find information when using the World Wide Web. However, limitations existed in the methods used to assess user performance. This experiment investigates alternative factors in more detail. It examines the use of age, cognitive characteristics, and Internet usage on the browsing experience of users when searching for information online.

4.1 Experiment Design

The aim of this experiment is to examine if factors that can be used to predict users' perceived disorientation and reported website ease of use within website search tasks. A study is presented in which older and younger adults participated in an information retrieval exercise to examine the perceived disorientation and reported website ease of use experienced when visiting a series of websites.

Participant Age Group, Internet Ability (Internet Usage and Internet Experience), and Cognitive Measures (Inductive Reasoning, Perceptual Speed, Memory Span and Meaningful Memory) were used as independent variables. Browsing Experience (Perceived disorientation and Reported Website Ease of Use) was used as dependent variables.

4.1.1 Participants

Twenty participants were recruited for this study. These participants were different than those recruited for Experiment 1. This consisted of 12 older adults (*M* = 73.66, *SD* = 9.11, *Range* 63-90) and eight younger adults (*M* = 22.12, *SD* = 3.18, *Range* 19-29). Older adults were recruited from a user pool of local participants, all of which have agreed to take part in HCI research [Dee and Hanson 2014]. Older adults were contacted by a user pool coordinator through phone and e-mail and invited to take part in the experiment. Younger adults were recruited through e-mail and university message boards and then added into the user pool database. All clarified in pre-screening that they had not taken part in any HCI research studies in the past 12 months.

4.1.2 Materials and Equipment

Demographic Information —Demographic information including participant age, education and occupational status were collected from participants through a questionnaire.

Internet Ability—Two questionnaires examining participant Internet Ability were used. The first of these examined participant Internet Confidence and consisted of 16 questions. These questions asked participants their confidence in completing a number of Internet based tasks, measured on a 5-point scale (Strongly Agree, Agree, Neither Agree nor Disagree, Disagree, Strongly Disagree). The second examined participant Internet Usage and consisted of 19 questions. These questions asked participants how often they would complete a number of Internet based activities and was measured on a 7-point scale (Everyday, Several Times a week, Several Times a month, Every few months, Less Often, Never). Responses within each category are combined and overall mean scores calculated.

Table 5 - Participant Testing Battery Summary

Measure	Ability Tested	Description
Letter Sets Test	Fluid Induction	Participants determine which of four letter sets is unrelated to the others
Meaningful Memory Test	Long Term Memory	Participants given a list of objects to study and then asked to select similar words after a 10 minute break

Number Comparison Test	Perceptual Speed	Participants required to inspect pairs of large numbers and indicate if the were the same or different
Auditory Number Span	Short Term Memory	Participants were read random-number sequences and asked to repeat each sequence
Internet Usage Questionnaire	Internet Usage	19-Item questionnaire assessing participant Internet usage
Internet Confidence Questionnaire	Internet Confidence	16-item questionnaire assessing participant Internet confidence

Cognitive Measures—Four cognitive measures were used to gather information on a subset of individuals' abilities. This consisted of the Letter Sets Test (measuring fluid induction) [Ekstrom et al. 1976], Number Comparison Test (perceptual speed) [Ekstrom et al. 1976], Meaningful Memory Test (long-term memory) [Cattell 1982], and Auditory Memory Span (memory span and working memory) [Ekstrom et al. 1976].

Testing of the Internet ability and cognitive measures was conducted under strict *'exam-like'* conditions and participants were free to withdraw at any time. Rest and refreshment breaks were provided between tests in order to reduce user fatigue. All testing was approved by the authors institutional ethics board.

Browsing Experience—A questionnaire based on work by Ahuja and Webster [Ahuja and Webster 2001] was used to gather information on users Perceived Disorientation and Reported Website Ease of Use. This questionnaire was designed to measure perceived disorientation and participant reported 'website ease of use' during online tasks and has been widely used since its introduction [Herder and Juvina 2004; Juvina and Oostendorp 2006; van Schaik and Ling 2012]. This questionnaire consisted of 10 questions, measured on a 7-point scale (Strongly Disagree, Disagree, Somewhat Disagree, Neither Disagree or Agree, Somewhat Agree, Agree, Strongly Agree).

Table 6 - Factor Analysis Comparison with Ahuja (2001)

	Ahuja (2001)		*Crabb & Hanson(2015)*		
	F.1	F.2	F.1	F.2	F.3
I felt lost	.70		.84		
I felt like I was going around in circles	.75		.85		
It was difficult to find a page that I had previously viewed	.78				.89
Navigating between pages was a problem	.75		.67		
I didn't know how to get to my desired location	.80		.82		
I felt disoriented	.72		.77		
After browsing for a while I had no idea where to go next	.73		.68		
Learning to use the site was easy		.90		.78	
Becoming skilful at using the site was easy		.88		.77	
The site was easy to navigate		.76		.79	

In order to validate the questionnaire responses gathered, a similar factor loading to that used by Ahuja & Webster [2001] was implemented. This is summarised in Table 6. The factor loadings of our data set are relatively similar to that of Ahuja and

Webster's with the one difference of *finding a page that was previously viewed* loading on an additional third factor. Factor 1 relates to users' perceived disorientation and Factor 2 relates to website ease of use. Factor 3 was removed as it only loaded on a single factor.

Task Question Set— 30 questions were created that prompted users to create a path through a website in order to complete an information retrieval task. One question was created for each website, with this creating a total of 30 different websites. Twenty-five of these sites were selected from the top 100 visited websites in the UK (according to Alexa[4]), split into five categories: health, shopping, news, governmental, and banking. Five additional websites were also selected that included information on attractions in the local area. Each task required participants to visit between two and five pages on the optimum path. However, the number of pages participants would visit increased if they used an alternative route. Example questions from this question set are shown in Table 7.

Table 7 - Example Questions from Task Question Set

Question Category	Website Address	Question
Health	http://www.nhs24.com	What groups of people are eligible for a seasonal flu jab?
Shopping	http://www.sky.com	How many channels are available in the Sky entertainment TV package?
News	http://www.bbc.co.uk	How many sports took place during the 2012 olympic games?
Governmental		
Banking	http://www.natwest.com	How much do Natwest cover for medical emergencies abroad with their travel insurance?
Local Area	http://www.dca.org.uk	What is the opening time for the Jute Café Bar?

Experimental Equipment—The experiment ran on an apple laptop computer (Macbook Pro Mid-2010[5]**)**, with the Google Chrome Browser being used. The laptop was placed in front of the researcher and the participant was given control through a 22" Widescreen Monitor, and a standard Microsoft Keyboard and Mouse. Monitor display was mirrored between the laptop and the additional monitor. Control of the *Data Collection System* was achieved through a tablet device handled by the researcher. This allowed the researcher to see the current question that is being asked, and additionally navigate through questions to control the flow of the study

4.1.3 Procedure

Participants were invited to take part in a one-to-one session where they were given a set of information retrieval scenarios to carry out online. Participants were firstly given a broad description of the aim of the study, being told that it was to look at the

[4] http://www.alexa.com/topsites/countries/GB

[5] http://support.apple.com/kb/SP584

problems that exist while searching online because of web usability issues and not the individual problems that a particular user may face. Participants were then given different scenarios to work through that are similar to tasks that they might carry out online. At the beginning of each task, the browser was set to the Google home page[6].

4.1.4 Analysis

An initial analysis of the two age groups (younger and older adults) showed differences between participants' Internet usage, Internet confidence and Inductive Reasoning. No age-related differences were noticed regarding perceptual speed, memory span / working memory, or meaningful memory. This was unexpected, as previous literature has shown that these metrics deteriorate with age and differences should be seen between these two groups [Horn and Cattell 1967].

Table 8 - Participant Demographic Information

	Younger Adult		*Older Adult*			*Comparison (α = .05)*
Ability Measures	M	SD	M	SD	*t(18)*	
Age	22.12	3.18	73.66	9.11	-15.26*	YA < OA
Internet Usage	48.00	10.85	29.92	12.86	3.27*	YA > OA
Internet Confidence	54.88	12.59	44.25	13.38	1.78*	YA > OA
Fluid Intelligence	23.63	2.26	18.17	2.82	4.57*	YA > OA
Processing Speed	46.63	6.04	45.08	6.94	.511	YA ≈ OA
Short Term Memory	6.88	2.94	7.25	1.91	-.547	YA ≈ OA
Long Term Memory	13.75	5.34	14.92	4.76	-.512	YA ≈ OA

* $p < .05$

A possible explanation (and limitation), can be explained in the educational background of the older adults recruited for this study. 9 of the 12 (75%) older adults reported having an education of Bachelors Degree or higher, with previous literature showing a link between educational background and these characteristics.

Analyses was designed to determine the impact that Age, *Internet Ability*, and *Cognitive Measures* had on understanding the *Browsing Experience* of this population. This was done to discover if any additional variance could be uncovered by examining these Internet and Cognitive factors on top of that discovered between age groups. Multiple regression was therefore used to analyse the data. Cognitive Measures, Internet Ability, and age were split into three separate models during analysis. Cognitive Measures and Internet Ability were normalised by dividing individual participant metrics by two times of the group standard deviation and age groups coded as a dummy variable (Younger Adult = 0, Older Adult = 1). This method, suggested by Gelman [2008], allows for a direct comparison between scalar and binary predictors.

In Model 1 only participant age was included as a measured variable. Model 2 expanded on this by including *Internet Ability*. Model 3 contained all *Cognitive Measures* along with the metrics outlined in Models 1 and 2. The three regression models were performed consecutively, with additional metrics being added with each

[6] http://www.google.co.uk

analysis. Three multiple regressions were performed in total, the first focussing on participants' perceived disorientation, the second on reported website ease of use, and the third on a combined *Browsing Experience* score.

4.2 Results

When examining the effectiveness of metrics to predict a user's disorientation and website ease of use, the data gathered suggest that age cannot be used as a metric to understand feelings of participant disorientation or website ease during information retrieval task. In Figure 1, Model 1 represents the variance accountable for only age. In this context, age cannot account for any variance present when analysing user perceived disorientation or users overall browsing experience. Age was only able to predict 1.6% of any variance when examining user feelings on a websites ease of use.

As previously stated, the younger and older adult categories were coded as 'dummy' variables in analysis. Using these two dichotomous groups is a limitation in this work as it may over inflate any results comparing these two groups. However, in this case, the results show that only a very small amount of variance regarding users browsing experience can be explained by the differences between these to age categories. This provides initial evidence to support the objectives set out in this work – examining the extent to which age accounts for variance in user satisfaction when completing information retrieval tasks. Similar results are reported by Czaja et. al [2006] who found that including age within the final step of a regression analysis did not significantly help in predicting individuals' technology usage.

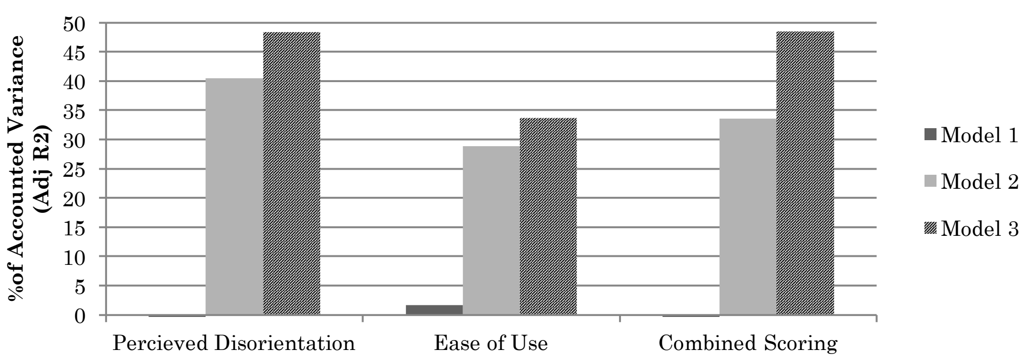

Figure 1 Model Comparison Summary

Model 2 improves on Model 1 by including participants' previous Internet usage and Internet confidence. This created a noticeable improvement (an increase to 40.5%) in the amount of perceived disorientation accounted for between groups. This indicates that it is possible to understand more about why an individual may feel lost completing information retrieval tasks by examining their previous experiences and confidence in using the Internet rather than relying on their age. Similarly, users feelings of website ease of use increased to 28.9% and their combined browsing experience increased to 33.6%. The inclusion of cognitive characteristics in Model 3 again provided an increase in the amount of variance accounted for.

A summary of regression analysis participant perceived disorientation is detailed in Table 9. Age as a single factor accounted for a very small amount of variance (Adj. R^2 = -.006) with the addition of technology factors causing an increment in Adjusted R^2 to .405. The addition of cognitive factors increases the Adjusted R^2 by an additional .008 to .484. In this final regression, it was found that key components, which correlated with perceived disorientation, were Internet confidence and processing speed.

Table 9 - Multiple Regression Model – Perceived Disorientation

	B	SE B	β
Model 1			
Constant	1.795	.155	
Age	.189	.200	.217
Model 2			
Constant	3.276	.425	
Age	-.168	.197	-.194
Internet Usage	-.238	.202	-.272
Internet Confidence	-.552	.174	-.632**
Model 3			
Constant	4.310	1.267	
Age	-.188	.292	-.216
Internet Usage	.021	.220	.024
Internet Confidence	-.646	.177	-.740**
Fluid Induction	-.051	.242	-.059
Perceptual Speed	-.404	.170	-.462*
Short Term Memory	-.063	.190	-.072
Long Term Memory	.359	.201	.411

Note: Adj R2 = -.006 for Step 1, Adj R2 = .405 for Step 2 ($p < .01$), Adj R2 = .484 for Step 3 ($p < .05$).
*$p < .05$, ** $p < .01$, *** $p < .001$.

These results suggest that when examining the amount of disorientation that is reported by an individual when carrying out an information retrieval task similar to the ones used in this work, a large amount of variability between participants is down to their confidence in using the technology, and also their current perceptual speed levels.

Summary analysis for reported website ease of use is presented in Table 10. Similar to perceived disorientation, age again accounted for a very small amount of variance (Adj $R^2 = .016$) with the addition of technology factors increasing Adjusted R^2 to .289. The attachment of cognitive factors increased Adjusted R^2 to .337 with Internet Confidence being the only significant factor present in the model.

Table 10 - Multiple Regression Model – Ease of Use

	B	SE B	β
Model 1			
Constant	3.060	.115	
Age	-.170	.148	-.261
Model 2			
Constant	2.153	.348	
Age	.033	.161	.051
Internet Usage	.092	.165	.141
Internet Confidence	.381	.142	.583*
Model 3			
Constant	1.044	1.075	
Age	.144	.248	.221
Internet Usage	-.103	.187	-.157
Internet Confidence	.447	.151	.683*
Fluid Induction	.186	.205	.284
Perceptual Speed	.285	.144	.437
Short Term Memory	.019	.161	.029
Long Term Memory	-.260	.171	-.398

Note: Adj R^2 = .016 for Step 1, Adj R^2 = .289 for Step 2 ($p < .01$), Adj R^2 = .337 for Step 3 ($p < .05$).

*p < .05, ** p < .01, *** p < .001.

This again suggests that when examining how easy users find a website to use, a large amount of variability exists due to user confidence in the technology. No significant results were found regarding user age, suggesting that the age group a user is in has very little to do with how easy or difficult they find a website to navigate around.

The final regression analysis collated the dependant measures into a single scoring, containing reported website ease of use and perceived disorientation. In this model, summarized in Table 5, age produced an Adjusted R^2 of -.023. This increased to .336 when including technology factors and again to .485 when including cognitive factors. In this final model, Internet Confidence and Processing Speed were seen to be significant factors.

Table 11 - Multiple Regression Model – Browsing Experience

	B	SE B	β
Model 1			
Constant	1.177	.123	
Age	.120	.159	.176
Model 2			
Constant	2.258	.354	
Age	-.129	.164	-.188
Internet Usage	-.134	.168	-.195
Internet Confidence	-.435	.144	-.632**
Model 3			
Constant	3.920	.998	
Age	-.281	.230	-.411
Internet Usage	.064	.173	.093
Internet Confidence	-.518	.140	-.752**
Fluid Induction	-.212	.190	-.307
Perceptual Speed	-.370	.134	-.538*
Short Term Memory	-.068	.149	-.099
Long Term Memory	.248	.158	.361

Note: Adj R^2 = -.023 for Step 1, Adj R^2 = .336 for Step 2 ($p < .05$), Adj R^2 = .485 for Step 3 ($p < .05$).

*$p < .05$, ** $p < .01$, *** $p < .001$.

Similar to a measure of only user perceived disorientation, this suggests that individuals' browsing experience is heavily influenced by their confidence in using technology, and not the overall amount of usage that they may report. Additionally, individuals' perceptual speed has shown to have an effect on the overall browsing experience, while age category does not have any effect

4.3 Discussion

In analysis, the main factors that could be used to predict levels of perceived disorientation in users were their confidence in using the Internet and also their perceptual speed. Figure 2 shows coefficients (*B*) for reported disorientation complete with 95% confidence intervals (an increase in value of 1 from any of the given metrics leads to a related change indicated by the bars, with 'error bars' indicating confidence that 95% of results would be between the two limits). This chart indicates that higher levels of Internet confidence and processing speed lead to reductions in perceived disorientation. From this, it can be inferred that an increase in confidence in using technology has a direct correlation on feelings of low perceived disorientation when completing information retrieval tasks online, with similar results appearing with their processing speed. An interesting point to note here is that no meaningful correlation was found between the amount of previous experience that an individual has in using the World Wide Web and any feelings of perceived disorientation. Significance is placed more on the confidence in using technology.

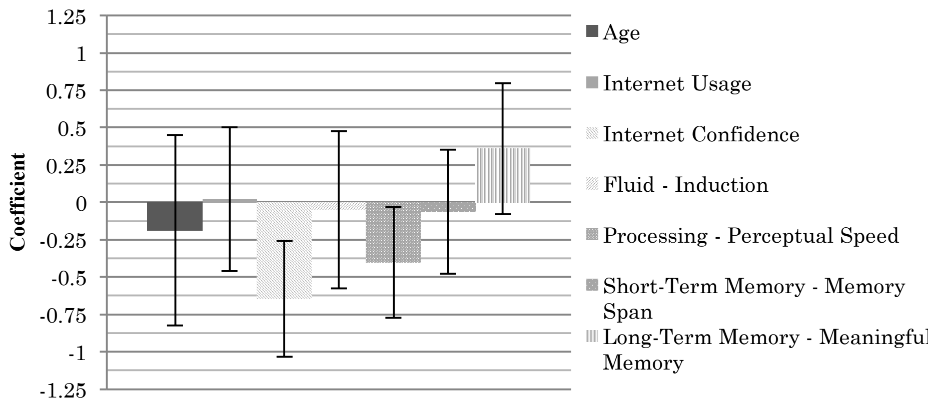

Figure 2 Coefficient for Perceived Disorientation with 95% Confidence Intervals

A slight difference was found when examining the reported website ease of use of participants. It was found that only Internet confidence played a significant part in determining whether a website was easy to use when performing information retrieval tasks. All other metrics had 95% confidence intervals which spanned both sides of 0, indicating that they could not accurately determine whether they may have a positive or detrimental effect on the reported ease of use of a website.

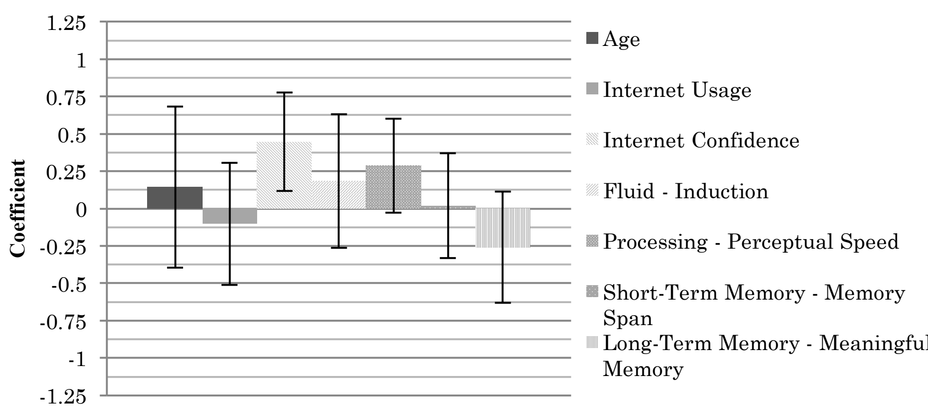

Figure 3 Coefficient for Ease of Use with 95% Confidence Intervals

Combining perceived disorientation and reported ease of use into one metric examining overall browsing experience creates results similar to that of perceived disorientation, with both Internet experience and perceptual speed producing significant correlations. No other factors contributed significantly in this model. This indicates that when examining the overall browsing experience of an individual when completing information retrieval tasks, a large amount of variance can be accounted for by again focusing on the previous confidence that a user has in using the Internet, and also the mental quickness that is attached to levels of user perceptual speed.

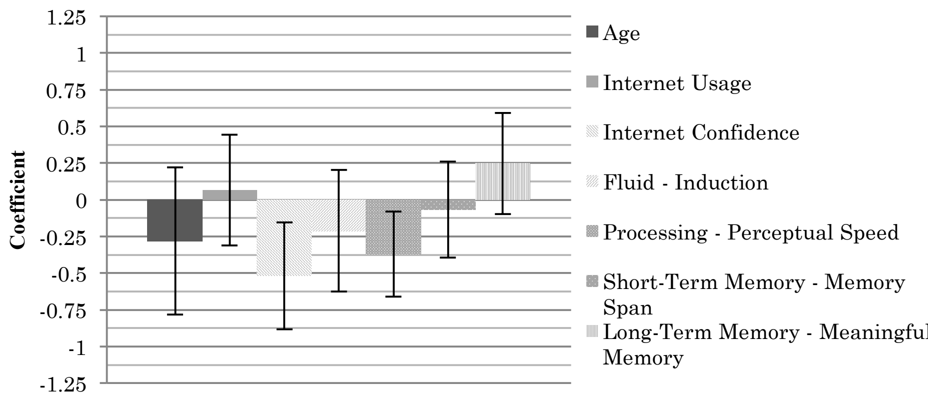

Figure 4 Coefficient for Browsing Experience with 95% Confidence Intervals

It was found in all three of the regression models that individuals' Internet confidence can account for a large amount of the variance that is associated with the perceived disorientation, website ease of use, and overall browsing experience of individuals when completing information retrieval tasks. Additionally, it was found that individuals' perceptual speed can influence their perceived disorientation and overall browsing experience. However, in all cases, age was unable to account for any variance and could not be used to predict any aspect of users browsing experience when completing this study.

4.4 Conclusions

This experiment has provided evidence to support the concept that age cannot be used as a metric when examining the browsing experience of individuals. Factors such as individuals' previous confidence in using the World Wide Web and their perceptual speed are more significant contributors to understanding feelings of disorientation and perceived website ease of use. These factors can be used to account for a substantial amount of variance. While this has been examined before regarding user performance (for example [Czaja et al. 2001] and [Sharit et al. 2011]) the novelty in this approach is that significant differences were found when examining search experience.

From this, it is recommended that cognitive factors and Internet usage demographics should be used within the analysis of user experience when completing online activities rather than relying on user age. The experiences of users in terms of perceived disorientation and reported website ease of use, cannot be predicted by analysing age and instead, users' confidence in using technology and their perceptual speed can provide a better explanation.

5. OVERALL DISCUSSION

The first experiment in this work examined how users' previous Internet usage and fluid intelligence can be used to understand the browsing habits of individuals. It was found that an individuals' previous Internet usage could be used to find significant differences in objective measures such as task completion time.

Users with high Internet usage are more efficient than those with low Internet usage. High Internet usage participants would spend less time on a search result page before selecting a link than low Internet usage participants, and would also visit more pages overall. Additionally, it was observed that participants with high Internet usage would use a comparable number of mouse clicks to those with low Internet usage, suggesting that they are either making less 'misclicks' on a page, or are not using as many interactive page features than participants with low Internet usage.

Age based differences were apparent in objective performance between older and younger adults. While no significant difference was found in the overall search engine usage between older and younger adults, it was found that younger adults visited more pages per minute than older adults, yet their average clicks per minute was comparable. This finding is very similar to that comparing high and low Internet usage older adults, and again suggests that these younger adult participants are either performing less mis-clicks during the study, using a combination of mouse and keyboard actions, or are using less interactive page elements during a study session.

The second experiment aimed to determine what user-based metrics, apart from age, can be used to understand the browsing experience of individuals. Age, Internet abilities, and cognitive characteristics were used to examine the perceived disorientation, reported website ease of use, and overall browsing experience of users.

User age has a very small effect when predicting users' browsing experience. All regressions within this study reported that age could not account for a significant amount of variance that is attached to participant perceived disorientation, reported website ease of use, and overall browsing experience. As such, one of the key findings from this study, and a recommendation for future HCI work, is that age cannot be used as a grouping variable when examining the browsing experience of individuals.

Internet Confidence, rather than Usage, is important in predicting browsing experience. While the amount of usage that individuals have in using a particular technology may increase their speed at completing tasks, the finding in this work suggests that it is their *confidence* in using technology that has an impact in their overall browsing experience. It is therefore suggested that a possible method of increasing the browsing experience for users is to attempt to invoke feelings of confidence an a particular service from an early stage, in order to make users feel more comfortable in using them.

Inductive Reasoning did not show to be a predictor of Browsing Experience. A surprising outcome from this work surrounds inductive reasoning, and its inability to act as a predictor of browsing experience. A large amount of literature in the past has examined fluid intelligence as a predictor of user performance, and Inductive reasoning is one of the 3 sub-abilities in this measure. This work found that while higher levels of inductive reasoning pointed towards less participant disorientation and a higher ease of use scoring, this was not at significant levels. A possible reason for this may be down to this work using a more subjective measure of performance, and that measures such as inductive reasoning are more key in objective performance metrics such as task completion time.

Perceptual Speed could be used as a predictor of determining participant Browsing Experience. The processing speed sub-ability, perceptual speed, was successfully used as a predictor of user browsing experience. Higher levels of perceptual speed, resulted in lower levels or perceived disorientation, high levels of reported website ease of use, and higher levels of overall browsing experience. These findings suggest that the mental quickness that is associated with this ability, can be utilized in order to quickly understand links between information retrieval questions, and the possible routes through a website. However, caution must be applied as high levels of processing speed have been shown to correlate with high education levels in an individual, and this may in turn produce a secondary effect.

Overall, the findings from this study suggest that Internet confidence and perceptual speed can be used to more accurately understand an individuals browsing experience than by examining their age.

5.1 Implications of Results

A key implication for research practice arising from this work surrounds the use of age as a grouping variable within future studies. This work has shown that age cannot be used as a suitable metric to distinguish between individuals when examining their browsing experience, and as such, further questions must be asked regarding its usage as a suitable metric when distinguishing between individuals in both the HCI and User Experience fields. While age can be used to distinguish between different generational groups, and this may be beneficial in study design, analysis should consider alternative metrics such as participant confidence in using the technology or service being tested. This method may provide additional information into the reasoning surrounding experiences of individuals before assuming that age based differences occur.

Additionally, and of importance when examining cognitive abilities, this work has shown that subjective measures, such as perceived disorientation and browsing experience, can be used as alternative measures to understand user performance rather than relying on objective measures such as task completion time.

One of the key findings from the second experiment suggested that Internet confidence is a key measure in accounting for the perceived disorientation, reported website ease of use, and overall browsing experience of an individual. This may have implications for future user training methods. A focus on increasing the confidence that individuals have in using a particular service will increase their overall experience in using it. This approach, opposed to providing users with information on how all aspects of a system works, may provide individuals with a higher level of satisfaction, improving their experience in using a service and in turn may also reduce the amount of assistance needed in the future and increase technology retention rates.

5.2 Limitations and Future Work

The first experiment presented in this work was used to develop an understanding into how participant Internet Usage and Inductive Reasoning can affect performance. In this experiment, a total of 18 users were recruited, with this being split into 12 older adults and 6 younger adults. Older adult participant were then further split into users with high/low Internet usage, and fluid intelligence. This low number of participants reduces the overall statistical power of the experiment. Additionally a further limitation arises in the sample choice used in this study. The research was conducted with participants that could be described as *extreme* values of independent metrics. Users were recruited based on high and low age levels, fluid intelligence, and Internet usage. Users that had 'average' levels were disregarded. Focusing on these dichotomous groupings was chosen to highlight the differences that were apparent in the browsing experience between these different population groups. An extension of this work would therefore be to include users that do not fall into these extreme categories, and instead examine the continuum of users in order to discover if any additional changes occur.

The second experiment in this paper aimed to discover if participants perceived disorientation, reported website ease of use, and overall browsing experience could be accounted for by analyzing their age, Internet, and cognitive abilities. During preliminary analysis, it became apparent that there was no significant difference in the processing speed, short-term memory, and long-term memory measures between the older and younger adults in this work. This may be down to the sample recruited being very highly educated. In our sample, 75% (9 participants) reported achieving a bachelor level degree or higher. Compared to Czaja et. al [2006] where 33% of their sample reported post-college degree and 22% reported college level degree. This limitation is amplified by the low sample size used in this work. A further limitation in this work lies in the number of independent metrics used in analysis when compared to the overall sample size of the population used. With a total of 20 participants and 7 independent measures in regression, caution must be applied to the findings. This imbalance in independent measures to participants severely hurts the power of any results obtained. Bonferroni adjusted significance values were however used through this experiment to help compensate for Type-I error. Whilst caution must therefore be applied to these findings, extending this work to increase statistical power could be achieved by recruiting a wider range of participants.

6. CONCLUSIONS

This work has explored the use of Internet and cognitive metrics as an alternative to age when carrying out website usability studies. The main finding to arise is that when subjective metrics such as participant feelings or browsing experience are being measured, age is not a suitable metric to distinguish between users. While caution may be applied to the overall results due to the low sample sizes used, this work suggests that Internet confidence and perceptual speed are suitable alternatives to measure differences in user browsing experience. It may be possible to use these measures in future usability research as an alternative to participant age when grouping individuals.

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