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Age, Technology Usage, and Cognitive Characteristics in Relation to Perceived Disorientation and Reported Website Ease of Use

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ABSTRACT
Comparative studies including older and younger adults are becoming more common in HCI, generally used to compare how these two different age groups will approach a task. However, it is unclear whether user 'age' is the underlying factor that differentiates between these two groups. To address this problem, an examination into the relationship between users' age, previous technology experience, and cognitive characteristics is conducted. Measures of perceived disorientation and reported ease of use are used to understand links that exist between these user characteristics and their effect on browsing experience. The presented research found that age accounts for as little as 1% of all disorientation reported. Further, it showed that cognitive ability and previous technology experience significantly affected perceived disorientation. These results argue for the inclusion of metrics regarding cognitive ability and previous technology experience when analyzing user satisfaction and performance in Internet based studies.

Categories and Subject Descriptors
H3.3 Information Search and Retrieval: Search Process. H.5.2. User Interfaces – Theory and methods; J.4 [Computer Applications]: Social and behavioral Sciences – Psychology.

General Terms
Measurement, Human Factors.

Keywords
Older Adults, cognitive psychology, HCI, web search, search strategies.

1. INTRODUCTION
The UK Office of Communication (Ofcom) report that over 50% of adults aged 65-74 and 25% of those aged 75+ now have access to the Internet [33]. With a growing number of adults using this technology comes a challenge in designing interfaces that this diverse population group can use. However, calling this cohort of users a single 'group' may cause problems - the methods and skills used by one of these users might well be completely different to that of another [21].

Differences have been found in the strategies used by older and younger adults in completing computer based tasks [4, 9, 16]. Users' abilities can change greatly over time and these changes can differ depending on both the individual and the culture in which they live [19]. How important, then, is 'age' in determining the experiences that users' may have when searching online? Would metrics other then age perhaps provide richer information? In this paper, we examine the use of age as a predictor of users' perceived disorientation and reported website ease of use. We report on a study in which older and younger adults participated in an information retrieval exercise to examine the perceived disorientation and reported website ease of use they experience. We then use a combination of multiple regression and fixed effect models to determine the suitability of users' age, cognitive characteristics, and previous technology usage in relation to these two metrics. Perceived disorientation and reported website ease of use is obtained from participants through self-reported user data, relying on first hand participant information rather than inferred experience metrics that can be obtained through log-file analysis.

2. RELATED WORK
A wide body of work exists that examines the design needs of older adults. However, this can focus on a 'deficit model' attached to aging, concentrating on general declines in vision, reduction in working memory, and use of slower movements [28]. Such deficit models have been used to create 'age' based guidelines that recommend the use of bigger text, larger buttons, and simpler websites [24]. A problem exists in that 'senior-friendly' adaptions to websites assume that the changes made will then allow older adults to successfully use the Internet based on a standard set of age-based assumptions. This presents an issue, as older adults are a dynamic population with differing ability levels that can change highly between individuals.

One of the most common alternatives to using age as a metric is previous technology usage [9]. This can be measured in different ways with the most prevalent being self-reported information. Possible implementations involve the use of questionnaires allowing users to report on aspects relating to technology usage, experience, and comfort. When examining the relationship between technology experience and task performance, older adults with high levels of previous technology experience have shown to have higher levels of performance in data-entry, file modification, and inventory management tasks than those with low levels of previous technology experience [8].

Table 1 - Participant Internet and Cognitive Comparisons

Ability Measures	Younger Adult M	Younger Adult SD	Older Adult M	Older Adult SD	t(18)	Age Group Comparison (α = .05)
Age	22.12	3.18	73.66	9.11	-	-
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

A powerful alternative to user age more related to ability is to examine individuals' cognitive characteristics. One area of cognitive psychology that has shown to have promise in HCI surrounds fluid intelligence - the ability of an individual to adapt to a situation based on their problem solving skills [26]. Fluid abilities can also include aspects such as short-term memory, speed of processing information, and problem solving abilities. The process of aging results in many changes in cognitive abilities with fluid attributes diminishing as individuals get older [25]. These changes can have a profound effect on individuals' skill in understanding new technologies, and to efficiently carry out tasks. Technology, therefore, needs to be designed to optimize a person's capabilities, while also compensating for their weaknesses [22]. Differences have been found to exist in the search strategies used by older and younger adults, with younger adults relying on system interface features when searching while older adults rely on a broad range of features [4]. It is possible, however, that these 'age' differences between older and younger adults are related to other characteristics, as clear links have been drawn between demographic data, cognitive abilities, and computer usage [9].

Fluid intelligence has been previously used to examine user task performance although the results from this have been varied [5, 37]. A decline in fluid cognitive abilities has been shown to relate to a decline in the reformulation of information retrieval requests [13] – especially important when using search functionality on websites. Combined with fluid intelligence, other cognitive factors have been successfully related to task performance including processing speed, short-term memory, and long-term memory. These factors have been used both as a combined cognitive ability scoring [5, 7] and also as individual factors in their own right [15, 30, 32, 35, 40].

In this work, the roles of age, user Internet abilities, and cognitive factors in relation to user online satisfaction levels are explored. Firstly, chronological age is analyzed to determine its relationship to perceived disorientation. Internet experience and Internet confidence are then included to understand if they can account for any additional variance. Finally, users cognitive characteristics are included to examine the combined relationship between these factors and perceived disorientation. This work attempts to gain an increased understanding into the use of these experience and cognitive based metrics when focusing on user browsing experience rather than performance.

3. METHODOLOGY

The main aim of this work is to consider how the inclusion of metrics other than chronological age could be used to enhance the understanding of how browsing experience can change between users when searching for information online. While previous research in this field has focused on user performance, we examine the effect that these factors have on overall browsing experience.

One of the most common problems faced by users when searching online it that of disorientation [31]. There are clear links between the methods used to navigate though a website and the tendency for users to lose their sense of location [39]. Many studies have tried to infer disorientation levels through the use of browser log information, rather than measuring users' feelings [1]. We use this second approach by gathering Likert scored data from participants within an information retrieval study. Sandelands and Buckner [34], among others, argue that the best method of gathering participant feelings is through quantitative responses and not qualitative work. This questionnaire was designed to measure perceived disorientation during online tasks and has been widely used since its introduction [23, 27, 38]. We use this rationale to support this methodology.

Ethical approval for all areas of this work was obtained through a university ethics procedure.

3.1 Participants

20 participants were recruited to take part in a user study examining perceived disorientation and reported website ease of use within information retrieval tasks. This consisted of twelve 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 within a group of volunteers in the local area who have all expressed an interest in participating in academic research. Younger adults were recruited through e-mail and university message boards. All clarified in pre-screening that they had not taken part in any HCI research studies in the past twelve months.

3.2 Procedure

All participants were invited to take part in a group session to gather demographic and cognitive information. Four separate sessions were used allowing for participants to be split into smaller, more manageable groups. Younger adults were tested separate from older adults. Participants completed a total of four cognitive tests and two technology based questionnaires. Details of these tests are given in Table 2. These were a subset of tests used as part of the CREATE battery of testing [9]. Table 1 shows that there was a significant age-based difference between, Internet usage, Internet confidence, and fluid intelligence. No group-related differences were noticed regarding processing speed, short- term memory, or long-term memory. This causes a limitation in this work, as it would normally be expected to find significant differences between all of these factors [9].

Participants were then invited to take part in a second session where they completed a number of information retrieval tasks. These tasks were designed to test an individual's ability to find

Table 2 - Participant Testing Battery Information

Measure	Ability Tested	Description
Letter Sets Test [14]	Fluid Intelligence	Participants determine which of four letter sets is unrelated to the others
Meaningful Memory Test [20]	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 [14]	Processing Speed	Participants required to inspect pairs of large numbers and indicate if they were the same or different
Auditory Number Span [14]	Short Term Memory	Participants were read random-number sequences and asked to repeat each sequence.
Internet Usage Questionnaire [9]	Internet Usage	19-item questionnaire assessing participant Internet Usage
Internet Confidence Questionnaire [9]	Internet Confidence	16-item questionnaire assessing participant Internet confidence

specific information on 30 different websites. Twenty-five of these sites were selected from the top 100 visited websites in the UK according to Alexa[1], 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.

In order to complete information retrieval tasks, participants were given short fact finding questions, asked to visit a particular website, and then navigate through the site until they had found an answer to the question. Participants were given the question though a Google Chrome plugin. This plugin was designed to be an unobtrusive add-on to the browsing environment and, when clicked, displayed a small pop up window that displays the current task along with any associated information that needed to be given to the participant.

Each question task required the participant to visit between two and five pages on the optimum path. However, the number of pages that a participant would visit increased if they use an alternative path.

Once an individual task had been completed, participants were asked to fill in a short Likert-scored questionnaire that focused on the their perceived disorientation for individual websites [1]. Task order was randomized between participants in order to reduce question bias and to ensure all websites were visited an equal number of times.

3.3 Analysis

Analysis is split into three separate sections. Firstly a multiple regression analysis technique is used to discover if any additional variance could be uncovered by examining previous technology usage and cognitive factors on top of that discovered for chronological age. Cognitive abilities, previous experience, and chronological age were therefore split into three separate models for analysis. *Model 1* uses only participant age as a measured variable. *Model 2* expanded on this by including Internet confidence and previous usage. *Model 3* contained all cognitive factors (fluid intelligence, processing speed, short-term memory and long-term memory) along with the metrics outlined in Models 1 and 2. Separate analysis was used for younger and older adults. All scores were normalized using Gelman's [18] method.

Secondly, a mixed-effect analysis is used to confirm findings from the multiple regression analysis. This is needed due to the repeated measures design of the experiment. Firstly a baseline model is created with individual participant identification only being used. A second model is then built with the addition of factors identified as significant within the linear regression. Beaumont [2] suggests that in order to compare between mixed-effect models, the difference in -2 Log Likelihood (-2LL) and the difference in degrees of freedom between models should be compared. This allows for the probability of models having a significant difference in degree of fit under a chi-squared distribution to be calculated. Significance being achieved using this method indicates that there is a valid difference between a baseline model and a second created model. However, as -2LL values are model dependent, no direct comparison can be drawn between any of the reported results.

Finally, an analysis of any significant confidence intervals identified is presented, with these using Type III estimates of fixed effects. Again, this is used to examine the effects of our metrics while also taking the repeated nature of the experiment design into account.

4. RESULTS

4.1 Accounted Variance Between Models

In all cases, we were able to improve the amount of accounted variance in our models with the addition of metric relating to users' previous Internet abilities and their cognitive characteristics. This is summarized in Table 4. The remainder of this section is used to highlight some of the more significant findings of this regression analysis.

User age has a very small effect when predicting users' browsing experience. When examining the effectiveness of metrics to predict users perceived disorientation, our results indicate that age can only account for a very small percentage of variance within our two groups. This is demonstrated in Table 4 where *Model 1* represents the variance accountable for only age. When examining older adults, age accounts for between 1-4% of the variance discovered. The same is true when examining younger adults; age again accounts for a very small amount of the variance. Even when the two user groups are combined, there is very little variance accounted for by age ($F(1,327) = 5.728$, $p < .05$, $R^2 = .017$, Adj. $R^2 = .014$). This provides initial evidence to support the objectives set out in this work, which was to examine the extent to which age accounts for variance in user satisfaction when searching for information online. Similar results to this have been provided by Czaja et. al [9] who found that including age in

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

Table 3 - Type III Tests of Fixed Effects and Estimates of Fixed Effects - Older Adult Disorientation

Parameter	Estimate	Std. Error	d.f.	t	F	Sig.	95% Confidence Interval Lower	Upper
Intercept	3.80	.440	7.3	8.63	74.50	<.001	2.769	4.832
Internet Confidence	-.559	.161	12.3	-3.4	12.07	.004	-.909	-.209
Processing Speed	-.597	.156	6.4	-3.8	14.56	.008	-.974	-.220
Long Term Memory	.689	.143	6.0	4.79	22.98	.003	.338	1.04

the final step of a regression analysis did not significantly help in predicting individuals' technology usage.

Older Adults' browsing experience can be highly predicted by their Internet and cognitive abilities. The second model in the linear regression analysis includes participants' previous Internet usage and Internet confidence. This created a noticeable improvement in the amount of perceived disorientation accounted for between groups, and especially so with older adults. For example, the amount of perceived disorientation accounted for in our older adult sample increases to 33%. This indicates that in order to understand why older adults may feel disorientated when navigating through websites, attention must first be placed on examining their previous experiences and confidence in using the Internet. The inclusion of cognitive characteristics in Model 3 again provided an increase in the amount of variance accounted for. In older adults this increased the accounted variance for perceived disorientation and reported ease of use by 9.5% and 2.2% respectively. The regression technique used in analysis was used to highlight the *unique* variance accounted for by cognitive characteristics in this third model, and not the overall variance. The low increase is therefore a result of high regression overlap, and not the inability of cognitive characteristics to account for variance.

Table 4 - Multiple Regression Summary

	df	F	R^2	Adj. R^2
Older Adults - Disorientation				
Model 1	1,132	1.83	.014	.006
Model 2	3,132	21.296***	.330	.314
Model 3	7,132	13.294**	.425	.393
Older Adults – Ease of Use				
Model 1	1,132	6.408*	.046	.039
Model 2	3,132	5.588***	.114	.094
Model 3	7,132	2.835**	.136	.088
Younger Adults - Disorientation				
Model 1	1,189	2.87***	.015	.010
Model 2	3,189	6,75***	.098	.084
Model 3	7,189	9.83***	.274	.246
Younger Adults – Ease of Use				
Model 1	1,189	13.76	.068	.063
Model 2	3,189	6.74***	.098	.084
Model 3	7,189	10.33***	.284	.257

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

Younger Adults' browsing experience is largely predicted by their cognitive abilities. Characteristics relating to previous Internet abilities only increase the amount of accounted variance in our younger adult perceived disorientation and reported ease of use models by 8.3% and 3% respectively. This is a very small amount in comparison to that reported by older adults. However, when examining the change in variance accounted between Model 2 and 3 in younger adults, including cognitive characteristics allows us to account for a much larger amount of perceived disorientation and reported website ease of; increases of 16.2% and 17.3% are observed. This suggests that younger adults are more reliant on their cognitive capabilities when completing information retrieval tasks rather than on past experiences.

This presents an interesting contrast between these two population groups. We have indicated when predicting older adults browsing experience both their previous experiences in using technology as well as cognitive capabilities can be relied on as suitable metrics, the same is not true when examining younger adults. This second group relies on cognitive abilities to a much larger degree in our models.

Mixed-effect model analysis confirms our findings. As previously discussed, a mixed-effect model analysis is needed to confirm any findings due to the repeated experimental design used. This successfully confirmed findings for both older adult models and for the younger adult disorientation model. Significance levels did not confirm findings regarding younger adult ease of use. This, however, is most likely due to Internet Confidence (p = .146) and Processing Speed (p = .251) showing Type III fixed effect significance levels that were far enough away from an acceptable level to be sure of their effect. Details comparing the mixed effect models can be found in Table 5 and further information regarding individual models in Tables 3, 6, and 7.

Despite a significant model being produced regarding older adult reported website ease of use, no individual factor provided statistically significant results – tests of fixed effects would therefore show the same low significance values. They are therefore excluded from further analysis.

Table 5 - Mixed Effect Model Comparison

	-2LL Baseline	-2LL Adjusted	χ2 d.f.	χ2 N	χ2 p
Older Adult Disorientation	258.77	243.60	6	15.17	.002
Older Adult Ease of Use	276.19	262.75	6	13.43	.037
Younger Adult Disorientation	314.36	301.91	4	12.45	.014
Younger Adult Ease of Use	332.92	332.35	6	10.57	.103

Table 6 - Type III Tests of Fixed Effects and Estimates of Fixed Effects Younger Adult Disorientation

Parameter	Estimate	Std. Error	d.f.	t	F	Sig.	95% Confidence Interval Lower	95% Confidence Interval Upper
Intercept	2.788	.854	14.6	3.26	10.66	.005	.964	4.611
Internet Confidence	.515	.206	8.13	2.49	6.236	.037	.041	.991
Internet Usage	.930	.233	8.60	3.99	15.99	.003	.400	1.461
Fluid Intelligence	-.545	.134	11.6	-4.0	16.35	.002	-.840	-.251
Short Term Memory	-.988	.365	6.10	-2.7	7.34	.035	-1.878	-.099

4.2 Effect of Individual Metrics

In our analysis of individual metric effects, we were able to again show that age cannot be used as a metric to understand users perceived disorientation and reported ease of use. A combination of factors must be considered when examining users' browsing experience. The remainder of this section discusses the importance of these additional factors.

A combination of factors must be considered when examining users' browsing experience. While some factors were seen to lower levels of perceived disorientation for users, there were also instances of factors increasing perceived disorientation. Figure 1 shows coefficients for significant user related metrics complete with 95% confidence intervals (a reminder that coefficients are standardized using Gelman's [18] method). This chart indicates that an increase in Internet confidence and processing speed lead to reductions in perceived disorientation. An increase in long-term memory, however, leads to an increase in perceived disorientation. These results suggest that an older adults confidence in using technology has a direct correlation with any feelings of disorientation that may occur. It is worth noting that no significance was found when analyzing technology usage and that significance is placed more on their confidence in using the technology.

Additionally, Figure 3 details significant factors found when examining younger adult reported website ease of use. In this instance, six metrics were included in the final mixed-effect model, with four of these showing statistical significance. Again, it is a combination of factors that relate to users' overall browsing experience and not one individual metric.

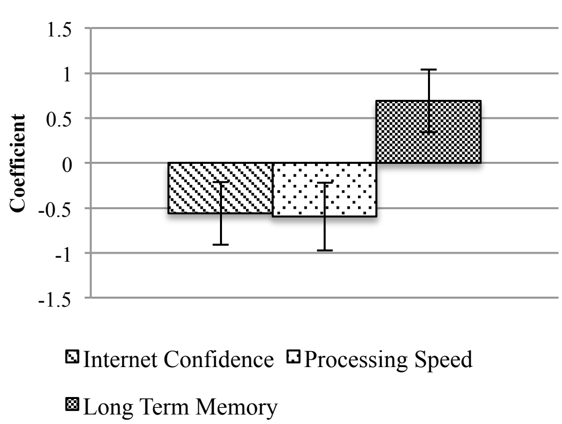

Figure 1 - Coefficient for Older Adult Disorientation with 95% Confidence Intervals

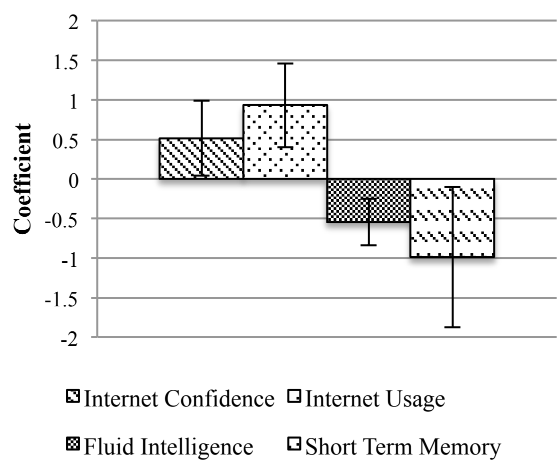

Figure 2 Coefficient for Younger Adult Disorientation with 95% Confidence Intervals

Internet Confidence shows to have differing effects between younger and older adults. Table 3 details information regarding significant factors related to older adult disorientation. In this, it is shown that an increase in Internet confidence relates to a decrease in perceived disorientation. Similar information is shown regarding younger adults in Table 6. However, in this instance an increase in Internet confidence relates to an increase in perceived disorientations. This difference between these two groups highlights that user characteristics can have differing effect between generations and perhaps that it is not a single factor that can be used to predict user disorientation, but a combination of factors.

This is not the first instance of unique differences being found between older and younger adults' online behavior. However, the majority of cases discuss how older adults click on fewer links, and spend more time completing a task [4]. In this instance, the difference between these two groups has highlighted how users' behavior (i.e. confidence) can have effect their overall disorientation in different ways between two generations of technology users.

Short Term Memory is a key predictor of younger adults' browsing experience. Significant metrics identified when examining younger adults reported website ease of use showed that short-term memory can be used as a key indicator in determining how easy younger adults find a website to navigate. Figure 3 indicates that as short-term memory increases, so does a website reported ease of use. This same relationship is seen for age and fluid intelligence, but not to as large a degree. Additionally, and seen in Figure 2, short-term memory again is

Table 7 - Type III Tests of Fixed Effects and Estimates of Fixed Effects Younger Adult Ease of Use

Parameter	Estimate	Std. Error	d.f.	t	F	Sig.	95% Confidence Interval Lower	95% Confidence Interval Upper
Intercept	1.297	1.303	19.1	.995	.991	.332	-1.429	4.025
Internet Confidence	-.540	.339	8.95	-1.5	2.532	.146	-1.309	.229
Internet Usage	-1.477	.505	7.47	-2.9	8.548	.021	-2.656	-.297
Fluid Intelligence	.7941	.202	7.44	3.91	15.33	.005	.320	1.267
Processing Speed	-.2522	.2032	7.77	-1.2	1.540	.251	-.723	.219
Short Term Memory	3.1454	1.263	7.29	2.48	7.285	.040	.180	6.11
Long Term Memory	-.9095	.3369	8.78	-2.6	7.285	.025	-1.674	-.144

the largest indicator in our model with an increase in short-term memory leading to a reduction in disorientation.

Fluid abilities are a key factor in determining users' browsing experience. In all regression models, fluid intelligence and processing speed were seen to lower levels of perceived disorientation (although sometimes this was not a statistically significant change). These two abilities greatly complement each other, with Flanagan and Ortiz [17] describing fluid intelligence to *"encompass mental operations that an individual uses when faced with a novel task…these include perceiving relationships and problem solving*" and processing speed as *"performing tasks fluently and efficiently…while keeping concentration*". Both of these factors are closely linked to information retrieval tasks, where users are required to deduce the correct pages to visit to find information on a particular topic, and also to maintain concentration to accomplish this successfully.

This result, however, is not a surprising outcome as previous research in this area has found similar relationships, albeit with stricter performance based measures such as task time. This therefore adds to a large body of work indicating the importance of fluid abilities as a characteristic to aid in examining user performance [3, 6, 10, 29, 37].

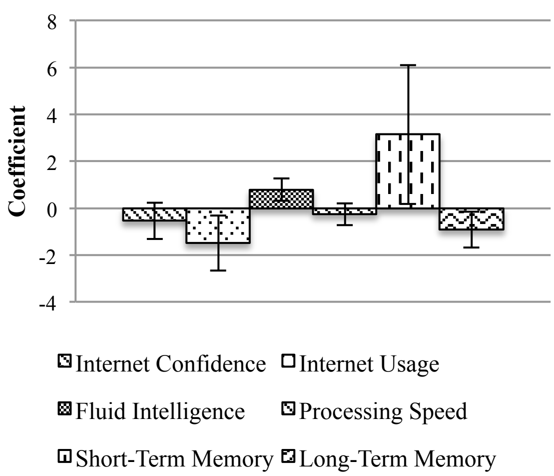

Figure 3 - Coefficient for Younger Adult Ease of Use with 95% Confidence Intervals

Increased long-term memory results in an increase in disorientation. Interestingly, regressions from younger and older adults displayed that increasing levels of long-term memory have an adverse effect on user perceived disorientation. This appeared for both younger and older adults, leading us to understand that this is a characteristic that is perhaps common to all users. This result does seem very counter-intuitive. However, similar results have also been discussed regarding user performance and long-term memory [40]. This is an aspect that therefore requires further attention in order to understand why this direction of result appears.

5. DISCUSSION

One of the main factors that appeared consistent throughout all of our analysis was the inadequacy of age to be used as measure of an individuals browsing experience. This finding has implications in the design of user studies, but also in the design of digital services. If user previous technology experience and cognitive abilities can explain to a greater degree why users may feel disorientated, what justification exists in continuing to design applications and services based purely age?

We have shown that by using Internet ability and cognitive metrics, we can greatly increase our understanding in what makes users feel disorientated when visiting websites. An interesting point to note is that our results indicate that around one third of user disorientation can be accounted for by user characteristics themselves; this work has not accounted for any variability present in individual websites. A further investigation surrounding any effect that the presence of individual website characteristics may have on user disorientation would therefore be advantageous.

However, a clear limitation exists in using these metrics. As previously discussed, users were invited to take part in two separate sessions to complete this study. The first of which was only used to gather information regarding their cognitive information and Internet ability. These tests also have to be administered under very strict conditions. This results in these metrics taking a large amount of time to obtain, and this occurring under stressful conditions for participants. This is therefore an area of interest for the future.

6. CONCLUSIONS

This paper has provided evidence that age is not a suitable metric to distinguish between users. Factors such as previous Internet usage and cognitive abilities can illuminate more significant contributors to ease of use than age alone. The primary finding to emerge from this study is that cognitive factors can be used to account for a substantial amount of variance within both older and younger adults, with factors acting as both negative and positive influencers. While this has been examined before regarding user performance [11, 12, 36], we have shown that similar results can be obtained when using hedonic measures such as search experience. This further demonstrates the ability of cognitive metrics to provide reasoning into how users interact with technology.

We have also shown that Internet experience metrics can be used to aid in understanding user disorientation, with an emphasis placed on users' Internet confidence rather than Internet usage. Complementing this finding, we have also shown that the amount of confidence that an individual has in using the Internet results in an increase in perceived disorientation in younger adults, but a decrease in disorientation in older adults.

From these results, we recommend that users' cognitive factors and Internet confidence demographics should be used within the analysis of online activities, rather than relying on user age. We have demonstrated that when examining the experiences felt by users, age is a very limited metric in terms of developing an understanding of why users are reporting feelings of disorientation and ease of use. A much greater understanding can be achieved by including cognitive factors and Internet based demographics.

7. ACKNOWLEDGMENTS

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