# The Use of Age, Technology Usage, and Cognitive Characteristics in Relation to User Perceived Disorientation

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## Problem and Motivation

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 [24]. 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 user online might well be completely different to that of another [14]. Users' abilities can change greatly over time and these changes can differ depending on both the individual and the culture in which they live [13].

Differences have been found to exist in the strategies used by older and younger adults in completing computer based tasks, with younger adults relying on system interface features when searching while older adults rely on a broad range of features [3]. 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].

How important, then, is 'age' in determining the experiences that users' may have when searching online, and would other metrics perhaps provide richer information? This work examines the use of age as a predictor of users' reported perceived disorientation. A study is reported in which older and younger adults participated in an information retrieval exercise to examine the perceived disorientation they experience. Multiple regression techniques are used to determine the suitability of users' age, cognitive characteristics, and previous technology usage in relation to levels of perceived disorientation.

## Background and 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 [21]. Such deficit models have been used to create 'age' based guidelines that recommend the use of bigger text, larger buttons, and simpler websites [17]. 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].

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 within Human-Computer Interaction (HCI) surrounds fluid intelligence - the ability of an individual to adapt to a situation based on their problem solving skills [18]. 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 [19]. 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 [15].

Fluid intelligence has been previously used to examine user task performance although the results from this have been varied [4, 5, 25]. A decline in fluid cognitive abilities has been shown to relate to a decline in the reformulation of information retrieval requests [11] – 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 [12, 22, 23].

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. What makes this approach novel is the examination of user browsing experience, rather than user performance during analysis.

## Approach and Uniqueness

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. Specifically, when searching for information online. While previous research in this field has focused on user performance, this work takes a more hedonic approach and examines the effect that these factors have on users' overall browsing experience.

20 participants were recruited to take part in a user study examining perceived disorientation 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.

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 to older adults. Participants completed a total of four cognitive tests and two technology based questionnaires. This consisted of tests measuring users fluid intelligence, processing speed, long-term memory, short-term memory, and Internet usage and confidence.

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 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.

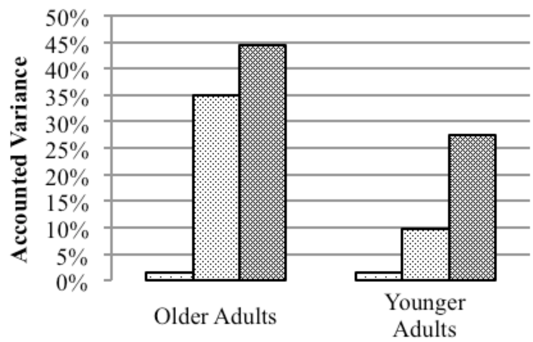
In order to complete information retrieval tasks, participants were given short fact finding questions, asked to visit a particular website, and then navigate through the site until they had found an answer to the question. Participants were given the question though a Google Chrome plugin. This plugin was designed to be an 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]. This questionnaire was designed to measure perceived disorientation during online tasks and has been widely used since its introduction [16, 20]. Task order was randomized between participants in order to reduce question bias and to ensure all websites were visited an equal number of times.

### Results and Contributions

The analyses were designed to determine the amount of impact that the selected variables had on levels of perceived disorientation. In particular, 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. In *Model 1* only participant age was included 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. Multiple regression was used to analyze the data with separate analysis occurring for younger and older adults. The three regression models were performed consecutively, with additional metrics being added with each analysis. Once multiple regression analysis was completed, a mixed-effect model analysis was used to confirm any findings due to the repeated measure design used during the study.




| | Older Adults | Younger Adults |
|---|---|---|
| Model 1 | 1.40% | 1.50% |
| Model 2 | 35% | 9.80% |
| Model 3 | 44.50% | 27.40% |

**Figure 1 Model Comparison Summary Showing Total R2 Values**

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 within Figure 1 where *Model 1* represents the variance accountable for only age. When examining older adults, age accounts for less than 1% of any variance associated with perceived disorientation. 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,

[1] http://www.alexa.com/

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

*Model 2* improves on *Model 1* by including 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. The amount of perceived disorientation accounted for within the older adult sample increases by over 33% when including these metrics. This indicates that it is possible to understand more about why older adults feel lost when visiting websites by firstly examining their previous experiences and confidence in using the Internet.

While the same is true for younger adults, it does not occur to such a large extent. Characteristics relating to previous Internet abilities only increase the amount of accountable variance by 8%. This does express the significance of these factors in analysis, but they are not as meaningful when compared to older adults. This presents an interesting contrast between these two population groups. While older adults satisfaction levels can be predicted largely by examining their previous use of the technology, the same is not true when examining younger adults and alternative measurements must be examined regarding their performance.

The inclusion of cognitive characteristics within *Model 3* again provided an increase in the amount of variance accounted for. Regarding older adults, this increase was approximately 10% and in younger adults this was 18%. When examining the results of older adults, an increase of such a low percentage may appear to be not as meaningful a result as younger adults but this is not the case. The regression technique used in analysis was performed in order to highlight the unique variance accounted for by cognitive characteristics within this third model, and not the overall variance. The low increase in older adults and high increase in younger adults is therefore a result of the varying levels of regression overlap, and not the inability of cognitive characteristics to account for variance.

When examining the change in variance accounted for between *Model 2* and *3* for younger adults, by including cognitive characteristics, a much larger amount of perceived disorientation can be accounted for than if only previous usage of technology were considered. This indicates that younger adults are more reliant on their cognitive capabilities when completing information retrieval tasks rather than on past experiences. This is different from older adults, where there is a larger reliance on both their previous experiences in using technology as well as cognitive capabilities.

*Older Adult Analysis*

**Table 1 Multiple Regression Model - Older Adult Reported Disorientation**

| | *B* | *SE B* | *β* |
|---|---|---|---|
| Model 1 | | | |
| Constant | 1.028 | .666 | |
| Age | .013 | .009 | .117 |
| Model 2 | | | |
| Constant | 3.297 | .658 | |
| Age | -.001 | .008 | -.007 |
| Internet Usage | -.580 | .140 | -.512*** |
| Internet Confidence | -.145 | .235 | -.076 |
| Model 3 | | | |
| Constant | 6.733 | 1.449 | |
| Age | -.020 | .011 | -.188* |
| Internet Usage | .310 | .322 | .273 |
| Internet Confidence | -.905 | .331 | -.477** |
| Fluid Intelligence | -.005 | .155 | -.003 |
| Processing Speed | -1.088 | .317 | -.699*** |
| Short Term Memory | -.144 | .173 | -.098 |
| Long Term Memory | .963 | .213 | .658*** |

*Note: $R^2 = .014$ for Step 1, $\Delta R^2 = .336$ for Step 2 ($p < .001$), $\Delta R^2 = .095$ for Step 3 ($p < .001$). *$p < .05$, ** $p < .01$, *** $p < .001$.*

A summary of the regression analysis for older adult perceived disorientation is detailed in Table 1. This consisted of the 12 older adults carrying out a total of 146 individual tasks between them. Age as a single factor accounted for a very small amount of variance ($R^2 = .007$) with the addition of technology factors causing an increment in $R^2$ of .33. The addition of cognitive factors increases the $R^2$ by an additional .095. In this final regression, it was found that key components that correlated highly with perceived disorientation were processing speed and long-term memory.

To further validate the results, a mixed effect model was used to compensate for the repeated measure design. Firstly a baseline model was created with individual participant identification only being used. A second model was 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. Comparing these two models, the baseline model has a -2LL of 258.769 (d.f. = 3) and the adjusted model 243.600 (d.f. = 6). This gives a $\chi^2$(d.f. = 3, N = 15.17) p = .002 from which we can conclude that there is a significant difference in the degree of fit between the two models. Type III Tests of Fixed Effects also verify the relationship between disorientation and each of the independent factors (shown in Table 2). Additionally, the 95% confidence intervals repeat the fixed variable directionality previously discussed within the linear regression analysis.

**Table 2 Type III Tests of Fixed Effects and Estimates of Fixed Effects - Older Adult Reported Disorientation**

| | | | | | | | *95% Confidence Interval* | |
|---|---|---|---|---|---|---|---|---|
| *Parameter* | *Estimate* | *Std. Error* | *df* | *t* | *F* | *Sig.* | Lower | Upper |
| Intercept | 3.800 | .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 | 1.040 |

While some factors were seen to lower levels of perceived disorientation for users, there were also instances of factors increasing perceived disorientation. Figure 2 details unstandardized coefficients for all user related metrics 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 an increase in age, Internet confidence, and processing speed all lead to reductions in perceived disorientation, with an increase in long-term memory leading to an increase in perceived disorientation. From this information, it can be seen that for older adults, an increase in confidence in using technology has a direct correlation with feelings of low perceived disorientation when visiting websites, with similar results appearing with their processing speed. No meaningful correlation was found between the amount of previous experience that an older adult has in using the Internet and feelings of perceived disorientation. Significance is placed more on their confidence in using the technology.

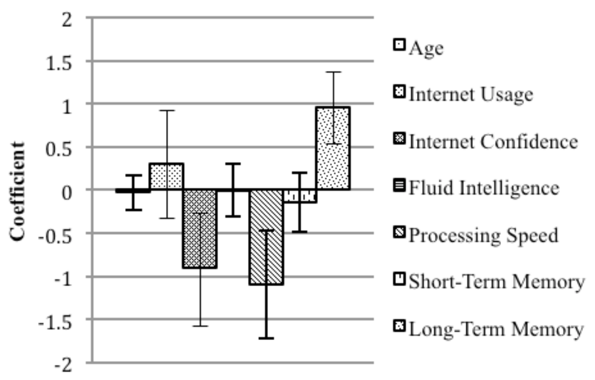



**Figure 2 Coefficient for Older Adult Disorientation with 95% Confidence Intervals**

*Younger Adult Analysis*

Summary of the regression analysis for younger adult disorientation is detailed in Table 3. This consisted of the 8 younger adults carrying out a total of 189 individual tasks between them. Age as a single factor accounted for a very small amount of variance related to perceived disorientation, with an $R^2$ of .015. The inclusion of technology factors then increased the $R^2$ by .083. This was then increased significantly with the addition of cognitive factors with $R^2$ increasing by an additional .176. In this final model it was found that Internet usage, Internet confidence, fluid intelligence, processing speed, short-term memory, and long-term memory could all used as significant predictors.

**Table 3 - Multiple Regression Model - Younger Adult Reported Disorientation**

| | *B* | *SE B* | *β* |
|---|---|---|---|
| Model 1 | | | |
| Constant | 2.338 | .342 | |
| Age | -.026 | .015 | -.123 |
| Model 2 | | | |
| Constant | .788 | .857 | |
| Age | .001 | .016 | .005 |
| Internet Usage | .411 | .176 | -320* |
| Internet Confidence | .006 | .155 | .005 |
| Model 3 | | | |
| Constant | 3.561 | 1.027 | |
| Age | -.065 | .036 | -.303 |
| Internet Usage | 2.010 | .401 | 1.563*** |
| Internet Confidence | .993 | .293 | .838*** |
| Fluid Intelligence | -.637 | .137 | -.399*** |
| Processing Speed | .427 | .188 | .321* |
| Short Term Memory | -4.672 | 1.178 | -1.293*** |
| Long Term Memory | .734 | .229 | .586** |

*Note: $R^2$ = .015 for Step 1, $\Delta R^2$ = .083 for Step 2 (p < .001), $\Delta R^2$ = .176 for Step 3 (p < .001). * p < .05, ** p < .01, *** p < .001.*

Similar to the approach taken when analyzing older adults, a mixed-effect model was used to compensate for the repeated measure design used in the experiment. A baseline model was firstly created with only individual participant identification being used. A second model was then developed with the addition of factors identified as highly significant (p < .001) within the linear regression (i.e. Internet Confidence, Internet Usage, Fluid Intelligence and Short Term Memory). Comparing these two models, the baseline model has a -2LL of 314.364 (df = 3) and the adjusted model 301.913 (df = 7). This gives a $\chi^2$(df = 4, N = 12.451) p = .014 showing that there is a significant difference in the degree of fit between the two models. Type III Tests of Fixed Effects again verify the relationship between disorientation and each of the independent factors. 95% confidence intervals echo the fixed variable directionality previously discussed within the linear regression analysis (shown in Table 4).

**Table 4 – Type III Tests of Fixed Effects and Estimates of Fixed Effects Younger Adult Reported Disorientation**

| *Parameter* | *Estimate* | *Std. Error* | *df* | *t* | *F* | *Sig.* | *95% Confidence Interval* Lower | 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 |

Differences occur when examining similar data regarding younger adults. This is summarized in Figure 3. In this case, fluid intelligence and short-term memory were found to decrease levels of perceived disorientation, but Internet usage, Internet confidence, processing speed and long-term memory were found to increase levels of perceived disorientation. This indicates that the most important factors for younger adults in achieving low levels of perceived disorientation online are high problem solving skills, and also the ability to recall information from a short term memory. From this, it is apparent that individual cognitive factors have an influence on how disorientated younger adults feel online. Short-term memory has a large influence on feelings of perceived disorientation, with an increase in short-term memory leading to a decrease in perceived disorientation. It was also shown that age showed to have no meaningful correlation. The 95% confidence intervals for age metric span both negative and positive values indicating that there is a large uncertainty in predicting its effect.

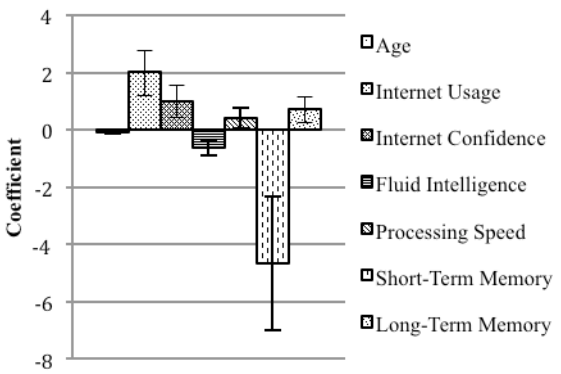



**Figure 3 Unstandardized Coefficient for Younger Adult Disorientation with 95% Confidence Interval**

Some major differences between older and younger adults also appeared during analysis. The most prominent of these surrounds the effect of Internet confidence between older and younger adults. It was found that high levels of Internet confidence result in greater feelings of perceived disorientation in younger adults, but lower levels of perceived disorientation for older adults. This clearly highlights that user characteristics have differing effect between generations. This same finding occurred, although not to as large an extent, with processing speed. Again for this metric, processing speed was seen to increase levels of perceived disorientation in younger adults, but lower perceived disorientation in older adults.

There were also noticeable similarities between the two groups. Fluid intelligence was seen to lower levels of perceived disorientation throughout all regressions (although sometimes this was not a statistically significant change). This adds to a large body of work indicating the importance of fluid intelligence as a characteristic to aid in examining user performance [4, 6, 10, 25].

## Conclusions

This work has provided evidence that chronological age is not a suitable sole metric to distinguish between users. Factors such as previous Internet usage and cognitive abilities can illuminate more significant 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, the uniqueness in this approach is that we found significant differences when examining search experience.

The second major finding concerned the amount of confidence that an individual has in using the Internet and that an increase in confidence in younger adults correlates to higher levels of perceived disorientation. The reverse of this was found when examining for older adults.

From these results, it is recommended that user' cognitive factors and Internet usage demographics should be used in the analysis of online activities, rather than relying purely on user age. It has been demonstrated that when examining the experiences felt by users in terms of perceived disorientation, age is a very limited metric in terms of developing an understanding of why users are reporting these feelings. A much greater understanding can be achieved by including cognitive factors and Internet usage demographics.

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