# A formal research of older adults' physical and cognitive traits in movement and selection tasks for interface design

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**Abstract**: The number of older adults is rapidly growing worldwide and online, and they are identified as a distinct group in HCI. An experiment was undertaken with 28 participants of different ages, studying the degree of applicability of Fitts' and Hick's laws. Seniors' predictable slower movement performance was supplemented by higher accuracy that was however revoked in selection tasks. Index of selection difficulty and selection throughput were proposed. Extended regression models for performance time and throughput, as well as suggestions regarding effect of interface elements size on seniors' performance were provided to aid justified design decisions.

***Key words: Interaction and Interface Design, Universal Design, Fitts' law, throughput***

## 1. Introduction

Older adults, who are generally defined as people aged 60 and over, remain one of the fastest growing demographic group both in the world and on the Internet. Worldwide, it is forecasted that by the middle of the XXI century the share of elder people in the population will triple and reach 20%, and in developed countries – even 1/3; and now this share increases most rapidly in Asia [14]. Online, their number is growing even more rapidly, e.g. in the USA the share of people aged 65 and over who use internet doubled during the last 6 years: from 20% in 2002 to 41% in 2008 [11]. Indeed, it was noted that existing stereotypes regarding elder people's lack of interest in using IT and Internet, anxiety towards technology or inability to learn it, are not supported by research [10]. However, as elder people generally have lower experience with information technologies and certain special needs arise as the result of even normal ageing process, it is estimated that computer interfaces usability for them is at least twice as low as for general, younger users [3, p. 4].

It is quite common to approach computer interaction needs of elder people via universal accessibility principles that are developed for people with limited capabilities – vision and hearing impairments, motor coordination and cognitive abilities problems, etc. However, in certain areas older adults were identified as a distinct user group having particular needs – such as ability to perform fine upper limb movements as well as execute related cognitive tasks [1, 7]. Still, few formal models exist that would allow designers to justify their decisions when developing interfaces for this user group. Thus, it was deemed necessary to further study traits of elder people related to HCI, and in this particular research we aimed to explore the applicability of such recognized findings in HCI as Fitts' and Hick's laws, individually and in conjunction, and provide extended models, if worthwhile, as well as other formalized recommendations allowing better interaction performance for seniors.

## 2. Method

### 2.1 Fitts' Law and its Application in Human-Computer Interaction

As rapid aimed movements are required to interact with most modern software interfaces, Fitts' law [4] remains one of the most important and recognized empirical findings in the field. The common expression of the law [14, p.755], following from Shannon's 17th Theorem is:

$$MT = a + b * \log_2(A/W + 1) = a + b * ID \qquad (1)$$

MT represents movement time required to reach a target of size (width) W at distance A, and the two constants (*a*, *b*) are generally found using regression analysis. The logarithm part is called the index of difficulty (ID):

$$ID = \log_2(A/W + 1) \qquad (2)$$

Thus, Fitts' law establishes relationship between movement time, distance and accuracy, via effective target size [13, p.756], and is known as robust and highly adaptive model. In HCI, the law is used both as predictive model, in particular for interface design, and for evaluation and comparison of various conditions and interface devices, such as mouse, trackball, touch screen, etc. [12, p.281], via derivative measure of throughput [13, p. 759].

Fitts' law generally provides a very good fit to empirical data, but no satisfactory psychomotor theory exists to explain the law [12, p. 286]. Also, some researchers reported cases when Fitts' law did not correspond well to the MT data for some special user groups or in special circumstances, such as for individuals with cerebral palsy [5].

### 2.2 Reaction Time and Hick's Law

Generally, several types of human reaction time are identified, of which two can be considered most important in HCI: simple reaction time, with one stimulus and one possible response, and choice reaction time, with several possible stimuli and corresponding responses. The latter is described by Hick's or the Hick-Hyman law [6], stating that reaction time (RT) required to choose from N equally probable choices is:

$$RT \sim \log_2(N + 1) \qquad (3)$$

Hick's law also has sound empirical evidences as well as practical implications for HCI and interface design. For example, it was argued in [8] that "wide" menu hierarchies are generally preferable to "deep" ones in terms of user performance time. In the same work, a combination of Hick's and Fitts' laws was used to model computer input task, by splitting it into choice component and movement component. In our study, similar approach was undertaken to model elder people's behavior when using computer mouse for movement and selection tasks.

### 2.3 Experiment

#### 2.3.1 Experiment Design and Procedure

I. Movement. The goal of the first part of the experiment was to explore the "physical" side of interaction with computer interfaces. The experiment was designed in accordance with recommendations for Fitts' law experiments, provided in [13]. It was within-subjects, with two groups of participants – elder people and younger computer users. The two other major independent variables were size of a square target (W) and distance to it (A). The values of A and W were chosen so that there were 7 different ID values ranging from 1.58 to 7.01; however, the number of outcomes for each combination of A and W was set to be lower than generally recommended, because of the exploratory nature of the study and the intent not to tire the seniors. The subjects were presented with two squares, a starting position and a target, which were positioned randomly in relation to each other on a computer screen to negate the effect of movement direction. The subjects were asked to click the starting position with a mouse pointer and then move the pointer to the target and click it, “as fast and as accurately as possible”. The movement time (MT) between the two clicks, was recorded, as well as exact coordinates of both clicks. If the second click was outside the target, error was recorded, and participant was taken to a next trial.

II. Selection. The second part of the experiment was aimed towards exploring “cognitive” (choice) and “physical” (movement) components of interaction in conjunction. The design was almost completely similar to the first part, but the target would become visible on the screen only after participant clicked on the starting position; and together with the target several false alternatives (of dissimilar shape and color) would appear. The subjects, “as fast and as accurately as possible”, needed to make a choice which object is the real target, then move the mouse pointer to it and click it, and total selection time (ST) between the two clicks was measured. The independent variables were size of a square target (W), distance to it (A) and the number of alternatives on the screen (N=2, 4 or 8). The values of A and W were chosen so that there were 6 different ID values ranging from 1.58 to 6.02.

Before starting the experiment, each subject did a practice run of trials with random combinations of A, W and N, until fully understanding the assignment and obtaining experience with the experimental environment. To measure and record the independent and dependent variables, an online application was developed with PHP and MySQL. The experiment sessions with the two groups of participants, elder and younger, took place with 21-days interval in a same room on same computer equipment, with monitor screen resolution of 1024*768 pixels.

### 2.3.2 Subjects

In total, 28 subjects took part in the experiment. Fifteen (4 male, 11 female) of them were elder people (age ranged from 56 to 74, mean=63.4, SD=5.26), recent graduates of 36-hour computer literacy courses held by People's Faculty of Novosibirsk State Technical University (NSTU). Another 13 subjects (5 male, 8 female) were recruited among NSTU Bachelor and Master students, as well as general staff (age ranged from 17 to 30, mean=23.9, SD=4.38). All subjects had normal or corrected to normal vision. Before the experiment, data regarding the participants' age and gender were gathered. Eight (53.3%) elder subjects reported having no experience in using computers or mouse before attending the computer literacy courses. All subjects participated in the experiment voluntary and for free, and prior to the experimentation informed consent was obtained.

## 3. Results

### 3.1 Movement Tasks (I)

The 15 outcomes for each of 7 ID values in the first part of the experiment resulted in 105 data for each participant, producing a total of 2940 data. The data were examined for validity and 52 (1.77%) data were removed from analysis – the outcomes where subjects made an obviously erroneous click far from a target or where the registered time was higher than 3000 ms, i.e. the movement couldn't be considered rapid, as required by the assignment and by Fitts' law. Among valid outcomes, the average level of error, i.e. when a target was missed, was 6%, which is consistent with a nominal error rate of 4% in Fitts’ law [13]. The mean value for movement time was 922 ms, SD=503. Table 1 shows mean values for movement time (MT) and error level ($E_I$) per ID.

Table 1. Mean movement time (MT) and error ($E_1$) per index of difficulty (ID)

| ID | 1.6 | 2.3 | 3.2 | 4.1 | 5.0 | 6.0 | 7.0 |
|---|---|---|---|---|---|---|---|
| MT, ms | 468 | 617 | 777 | 890 | 1039 | 1247 | 1425 |
| $E_1$, % | 3.4 | 5.6 | 4.6 | 4.8 | 5.9 | 6.8 | 11.0 |

### 3.1.1 Subjects' Characteristics

MANOVA was used to test the effect of subjects' characteristics such as subject group, gender and experience (for this factor, the analysis was done for elder participants only) on MT and $E_1$ (Table 2).

Table 2. MANOVA results (significance and est. marginal means) for MT and $E_1$ per subjects' characteristics

| | | All participants | | | | Elder[1] | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Group | | Gender | | Experience | | Gender | |
| | | Elder | Younger | Male | Female | Normal | Low | Male | Female |
| MT | Sig. | $F_{1,2884}$=890.9; **p<.001** | | $F_{1,2884}$=8.1; **p=.005** | | $F_{1,1523}$=121.4; **p<.001** | | $F_{1,1523}$=121.4; **p<.001** | |
| | Est. mean | 1156 ms | 642 ms | 874 ms | 923 ms | 1016 ms | 1370 ms | 1242 ms | 1144 ms |
| $E_1$ | Sig. | $F_{1,2884}$=11.7; **p=.001** | | $F_{1,2884}$=17.3; **p<.001** | | $F_{1,1523}$=3.7; p=.06 | | $F_{1,1523}$=16.2; **p<.001** | |
| | Est. mean | 3.7% | 7% | 3.4% | 7.3% | 5% | 2.4% | 1% | 6.5% |

### 3.1.2 Factors in the Experiment

The effect of the experimental conditions was analyzed independently for the two subject groups. Predictably, distance (A) had significant effect on MT for both elder and younger participants. At the same time, the effect of distance was not significant for the number of errors committed by neither seniors ($F_{6,1502}$=.9; p>.5), nor their younger counterparts ($F_{6,1336}$=1.2; p=.29). Size of a target (W), besides significantly affecting MT for both subject groups, also had significant effect on error level for both elder ($F_{4,1502}$=5.5; p<.001) and younger participants ($F_{4,1336}$=2.7; p=.03). Post-hoc analysis indicated that only W=8 px was significantly different in terms of committed errors, for both groups, and led to 10.2% and 12.3% errors for elder and younger subjects respectively. The interaction between distance to a target and its size was not significant for either of the subject groups.

### 3.1.3 Regression

Before attempting the Fitts' law regression, effective values were calculated for distance to the target and its size, in line with recommendations provided in [13, p. 755], to adjust the results for accuracy. Effective distance ($A_e$) was determined as real distance between the coordinates of the two mouse clicks on the screen. Effective target size ($W_e$) was calculated based on standard deviation (σ) of end-clicks, as recommended in [13, p.756], but σ was determined for each participant instead of for each condition. Then, effective ID ($ID_e$) was evaluated for each experimental condition based on (2), but for effective values of $A_e$ and $W_e$. The mean value of $ID_e$ was 3.83 (SD=1.8), and effective $ID_e$ was used instead of nominal ID in Fitts' law equations, the parameters for which were determined with regression, separately for elder and younger subjects:

$$MT_{eld} = 359 + 211 * ID_e, \ldots R^2 = .537 \quad (4) \qquad MT_{yng} = 132 + 134 * ID_e, \ldots R^2 = .639 \quad (5)$$

All the coefficients in the above models were highly significant (p<0.001) but as the $R^2$ values were relatively low, it was deemed necessary to include additional factor in the model, participant's age (T), as the previous analysis suggested its high importance. In the proposed model, 18 years are deducted from T, just to indicate the

[1] For elder subjects, also interaction between experience and gender was significant for MT ($F_{1,1523}$=6.8; p=.01)

approximate lower bond of this factor value. The extended model was built for subjects from both groups together, but seniors who had low experience were not included, to eliminate the effect of the experience factor.

$$MT = 4 + 154 * ID_e + 9 * (T - 18), \ldots R^2 = .694 \qquad (6)$$

### 3.1.4 Throughput

Throughput, which is a complete measure of performance, encompassing both movement speed and accuracy [13, p.760], was calculated for each subject as mean ratio between $ID_e$ and MT for each experimental condition. The mean value of throughput for all participants in the experiment was 4.58 (SD=1.46). ANOVA was used to test the effects of subject group, gender and experience on achieved throughput. Significant effects were found for subject group ($F_{1,22}$=98.1; p<.001) and experience ($F_{1,22}$=10.9; p=.003). Mean throughput for elder participants was 3.29 compared to 6.06 for younger ones. Experienced subjects achieved mean throughput of 4.93 vs. 2.77 for low-experienced ones.

A regression model was proposed for throughput (TP) with factors of subjects' age (T) and low experience (LE, either 0 or 1). The model incorporated both groups of participants, elder and younger, and had relatively high $R^2$:

$$TP = 6.308 - 0.998 * LE - 0.053 * (T - 18), \ldots R^2 = .924 \qquad (7)$$

### 3.2 Selection Tasks (II)

The number of outcomes for each participant in the second part of the experiment was 51, producing a total of 1428 data. Again, the data were examined for validity and 20 (1.4%) data were removed from analysis – the outcomes where subjects made an obviously erroneous click far from a target or where the registered time was higher than 3000 ms. Among valid outcomes, the average level of error was 6.8%. The mean value for selection time (ST) was 1049 ms, SD=444. Table 3 shows mean values for ST and error level ($E_2$) per ID and N.

Table 3. Mean selection time (ST, ms) and error ($E_2$, %) per index of difficulty (ID) and number of targets (N)

| N / ID | 1.6 | 2.3 | 3.2 | 4.1 | 5.0 | 6.0 | Mean |
|---|---|---|---|---|---|---|---|
| 2 | 842 (3.6%) | 965 (7.2%) | 1016 (6.4%) | 1064 (8.4%) | 1238 (7.3%) | 1467 (7.1%) | 1034 (6.6%) |
| 4 | 814 (4.8%) | 953 (2.8%) | 1016 (3.7%) | 1121 (9.5%) | 1259 (7.1%) | 1660 (14.3%) | 814 (5.7%) |
| 8 | 797 (4.8%) | 977 (6.4%) | 1020 (9.1%) | 1170 (8.4%) | 1328 (7.1%) | 1526 (24.0%) | 1061 (8.1%) |
| Mean | 818 (4.4%) | 965 (5.5%) | 1018 (6.4%) | 1118 (8.8%) | 1275 (7.2%) | 1552 (14.8%) | 1049 (6.8%) |

### 3.2.1 Subjects' Characteristics

As in the previous part of the experiment, a multivariate analysis of variance was used to test the effect of subject group and gender on selection time and number of committed errors. The results suggest highly significant effect of subject group on time ($F_{1,1404}$=365.8; p<.001), with estimated marginal means of 1238 ms for elder subjects vs. 814 ms for younger ones. The effect of subject group on error was not significant ($F_{1,1404}$=1.8; p=.18), in contrast to the first part of the experiment. It was noted that in the second part the error level increased for both groups of participants (for corresponding ID values, i.e. without considering outcomes with ID=7 of the first part). However, for younger subjects the error level growth was from 6.9% to 7.4% (7% increase), while for elder ones – from 3.6% to 6.3% (75% increase), and the increase was more notable for ID values of 4.1 and higher.

The gender factor remained significant for both selection time ($F_{1,1404}$=5.3; p=.022) and number of committed errors ($F_{1,1404}$=5.0; p=.026). As before, male participants on average were somehow faster, with 1001 ms vs.

1051 ms for female ones. The mean number of errors was 4.6% and 7.8% respectively. No significant interaction between the independent variables was observed.

### 3.2.2 Factors in the Experiment

For the two subject groups separately, the effect of independent factors (A, W and N) was analyzed. As in the first part of the experiment, distance to the target significantly influenced selection time for both elder ($F_{4,695}$=15.4; p<.001) and younger ($F_{4,611}$=30.1; p<.001) participants. Interestingly, in contrast to the first part, selection time required to complete the assignment (ST) did not increase linearly with A, but had its minimal values at A=128 px (Figure 1). As before, A did not significantly affect error rate ($E_2$) for either group.

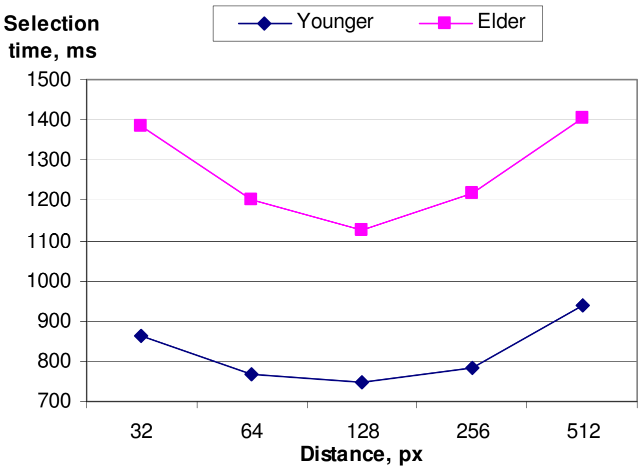


Figure 1. Selection time (ST) per distance (A)

Target size (W), besides significantly affecting selection time for both subject groups, also had significant effect on error level for both elder ($F_{3,695}$=3.6; p=.014) and younger participants ($F_{3,611}$=2.6; p=.054), although the significance was lower than in the first part of the experiment. Post-hoc analysis indicated that only W=8 px was significantly different in terms of committed errors, with 10.2% and 11.3% errors for elder and younger subjects. The analysis did not show significant effect of number of targets (N) on ST, for neither elder ($F_{2,695}$=0.2; p=.834), nor younger ($F_{2,611}$=0.6; p=.554) participants. However, N significantly affected $E_2$ for younger subjects ($F_{2,611}$=3.3; p=.039), with minimal value of .041 for N=4. No significant interaction between the independent variables was observed.

### 3.2.3 Regression

As in the first part of the experiment, effective index of difficulty ($ID_e$) was calculated for each outcome (2), based on effective distance ($A_e$) and effective target size ($W_e$). The mean value for $ID_e$ was 2.89, SD=1.28.

It was assumed that selection task completion time included choice reaction time (RT), presumably described by Hick's law, and movement time (MT), predicted by Fitt's law. Then, for each subject group a regression was attempted, with ST as dependent variable and $ID_e$ and *log*(N) as factors. It was found out that *log*(N) was not significant in the regression, neither for elder (p=.533), nor for younger (p=.112) participants. The regression equations for the corresponding groups had relatively low $R^2$:

$ST_{eld} = 820 + 151 * ID_e, \ldots R^2 = .180$ (8) $\qquad$ $ST_{yng} = 464 + 122 * ID_e, \ldots R^2 = .299$ (9)

As the number of targets was not significant for ST in neither ANOVA nor regression analysis, we proposed that RT in the experiment could be in inverse relation to target size (W). And indeed, this factor turned out to be highly significant in the regression, for both elder (p<.001) and younger (p<.001) participants:

$$ST_{eld} = 731 + 84 * ID_e + 4333/W, \ldots R^2 = .299 \quad (10) \qquad ST_{yng} = 417 + 76 * ID_e + 2732/W, \ldots R^2 = .426 \quad (11)$$

As $R^2$ values in (10) and (11), although higher than in (8) and (9), were relatively low, the factors of age (T) and low experience (LE) were included in the model built for both groups of participants:

$$ST = 302 + 78 * ID_e + 3625/W + 8 * (T - 18) + 275 * LE, \ldots R^2 = .551 \qquad (12)$$

The significance of all factors in the model was high (p<.001). As in the regression model proposed for MT (6), higher age and lower experience led to increased task completion time.

### 3.2.4 Index of Selection Difficulty

Based on the above assumption that selection difficulty is in inverse relation with target size (W), we introduced the index of selection difficulty (IDS) that took into account both the above factor and Fitts' ID (2):

$$IDS = ID_e + c / W \qquad (13)$$

Constant *c* characterizes the relative difficulty of target choice and of movement (Fitts'), and it depends of subjects' personal characteristics, experiment conditions, independent variables values (in particular, W) and so on. The IDS, thus proposed, increases as target size diminishes, and approaches Fitts' ID as target size grows. Based on the coefficients that we received in regressions (10) and (11), the values for *c* in our experiment, for elder and younger subjects respectively, could be calculated as the following:

$$c_{eld} = 4333/84 = 51.6 \quad (14) \qquad c_{yng} = 2732/76 = 35.9 \quad (15)$$

To find out what ratio of targets sizes would make selection difficulty equal for elder and younger participants, we would equate $IDS_{eld}$ with $IDS_{yng}$ (13):

$$ID^e_{eld} + 51.6 / W_{eld} = ID^e_{yng} + 35.9 / W_{yng} \qquad (16)$$

After substituting $ID_e$ with its expression (2) we would have:

$$\log_2(A^e_{eld} / W^e_{eld} + 1) + 51.6 / W_{eld} = \log_2(A^e_{yng} / W^e_{yng} + 1) + 35.9 / W_{yng} \qquad (17)$$

As we found out that the subject group didn't affect error level in the second part of the experiment, the ratios between nominal and effective target sizes (W and $W_e$) will be approximately the same for both of the groups. To verify if $A_e$ are equal for elder and younger participants, we ran independent samples t-test. The test showed no significance (p=.956), so the hypothesis that the samples means are equal could not be rejected. Thus:

$$\log_2(const / W_{eld} + 1) + 51.6 / W_{eld} = \log_2(const / W_{yng} + 1) + 35.9 / W_{yng} \qquad (18)$$

When solving this equation for $W_{eld}$ and $W_{yng}$, we would get:

$$W_{eld} = 1.42 * W_{yng} \qquad (19)$$

So, for selection difficulty for elder users to be identical to one for younger users, target had to be 42% larger.

### 3.2.5 Selection Throughput

By analogy with throughput for movement tasks (TP), we introduced throughput for selection tasks (TPS), as mean throughput for each of S subjects, which in turn is averaged over M experimental conditions:

$$TPS = \frac{1}{S}\sum_{i=1}^{S}\left(\frac{1}{M}\sum_{j=1}^{M}\frac{IDS_{ij}}{ST_{ij}}\right) \qquad (20)$$

To calculate IDS value for each outcome, we first needed to find out average *c* coefficient for all participants in the experiment. For this, regression equation was calculated, analogous to (10) and (11), but for all subjects:

$$ST = 588 + 79 * ID_e + 3573/W, \ldots R^2 = .240 \qquad (21)$$

Then, IDS in our experiment would be equal to:

$$IDS = ID_e + (3573/79)/W = ID_e + 45.3/W \qquad (22)$$

Mean value for IDS thus defined was 5.84, SD=2.76, while mean TPS was 5.88, SD=1.44. The correlation between TP and TPS per participants was quite high and amounted to .924. At the same time, t-test for paired samples showed that mean TP and TPS are different, both for elder ($p<.001$) and younger ($p<.001$) subjects.

ANOVA was used to find out if subject group, age and experience influenced his or her selection throughput. Subject group had significant effect ($F_{1,22}=33.1$; $p<.001$), as well as experience level ($F_{1,22}=4.2$; $p=.052$). Estimated marginal mean for TPS was 4.8 for elder participants, compared to 7.21 for younger ones. Experienced subjects achieved TPS of 6.25, while low-experienced ones – only of 4.33.

Regression model was proposed for TPS, considering factors of subjects' age (T) and low experience (LE). The model included data for both groups of participants, elder and younger, and had relatively high $R^2$:

$$TPS = 7.499 - 1.014 * LE - 0.049 * (T - 18), \ldots R^2 = .859 \qquad (23)$$

It is worth noting that coefficients for T and LE in the equation above were quite close to ones we got in the regression (7), for throughput for movement tasks (TP).

## 4. Conclusions

### 4.1 Elder People as a Distinct User Group in HCI

The results of the experiment undertaken to explore "physical" and "cognitive" traits of older adults in relation to HCI suggest that they indeed can be identified as a distinct user group. The difference in subject group was highly significant for both movement time and committed error. On average, it took elder participants almost twice as much time to complete movement tasks (1156 ms vs. 642 ms), but their accuracy was almost two times higher than one of their younger counterparts (3.7% errors vs. 7%). As for both groups the assignment was stated in exactly the same way, "as fast and as accurately as possible", it may suggest that seniors are prone to error-avoidance in their interaction with computers, even if at the cost of slower performance. Notably, elder subjects with low experience were even more slow and accurate (1370 ms and 2.4% error level). Consistently slower movement performance for older adults is widely confirmed, see [2] for example, but in that research equivalent error rates were reported. In selection tasks, subject group was significant for performance time, but not for error. Elder subjects increased their error rate by 75%, to 6.3%, approaching the rate recorded for younger participants, which increased only by 7%. Average performance time (for ID<7) for elder participants in the second part of the experiment increased only by 178 ms, while for younger ones the increase was 237 ms. The above two observations may suggest that elder subjects, when faced with necessity to make a fast choice, abandoned their "slower but surer" strategy. Additional research may be required to further investigate this phenomenon.

### 4.2 Basic HCI Laws Applicability and Regression Analysis

The regression analysis suggests that Fitts' law applicability to describe upper limb motor behavior of elder people can be confirmed, as the regression (4) was significant, and the value of $R^2$=.537 was close to one for younger subjects (5), $R^2$=.639, but smaller still. The intercept value in the model for elder subjects, a=359, although in line with generally accepted intercepts for Fitts' law of -200-400 ms [13, p.758], was still greater than the value for younger participants, a=132. As it is argued that large intercepts can be attributed to random variation in subject performance [13, p.772], the above two findings may suggest that the movement performance of older adults is more variable or that it is affected by factors not considered in Fitts' law. The $R^2$ values of Fitts' law models, (4) and (5), in the current research were relatively low for both groups, compared to other studies that generally report $R^2$ of .9 and higher [13, p.768]. It may be possibly explained by imperfections in JavaScript and/or Internet Explorer browser, which could introduce random bias in time measurements.

The number of alternative targets on the screen was not found to be significant for selection time, for neither subject group, which may suggest decreased effect of reaction time, described by Hick's law, on overall performance time. Indeed, other researchers (e.g. [8]) argued that Hick's law applicability in HCI may depend on a number of factors, such as what exactly is presented as alternative stimuli.

Extended regression models that were proposed for movement (6) and selection (12) time produced somehow better $R^2$ and may provide a useful insight for HCI re-searchers and interface designers, in particular by incorporating factor of subjects' age that deteriorated performance time in corresponding tasks.

### 4.3 Effects of Interface Element Size and Distance to it

Of the experimental conditions, distance to a target (A) and its size (W), only the latter had significant effect on error rate, which is in line with other research works [9, ch.2.2]. In particular, the smallest W of 8 pixels caused both groups of the participants to commit significantly more errors – for seniors, more than three times the average. Thus, interface designers may be advised to use interface elements sized at least 16 pixels on a 1024*768 screen. Also, based on (19), we could conclude that for selection difficulty for elder users to be identical to one for younger users, W in the experiment had to be 42% bigger, all other factors being equal.

Distance was significant for performance time in both parts of the experiment, but if for movement time the relation was almost linear, for selection time the minimal value was estimated at A equal to 128 px (Figure 1). For real interfaces, this may probably be extrapolated for cases when user doesn't know in advance the distance to a target element – e.g., for seldom used context menu. What is definite, however, is that in selection tasks the number of errors significantly increased for ID values of 4.1 and higher. Thus, interface designers may be advised to pick A and W so that ID is below this value.

### 4.4 Throughput and Index of Selection Difficulty

The average throughput (TP) value in the experiment, 4.58, agrees with the range of 3.7–4.9 reported in throughput studies comforting to ISO9241-9 standardized methodology [13, p. 784]. However, for elder participants mean throughput was only 3.29, and even 2.77 for low-experienced ones. Significant negative influence of age on throughput, as suggested by proposed regression model (7), was, in particular, confirmed in [2]. Interface designers may be advised to consider these findings when building dynamic interfaces, setting time-outs, etc.

As the number of alternative targets was not significant for selection time in the regression, a proposal was made to introduce index of selection difficulty (IDS), incorporating both Fitts' index of difficulty and target size. Further, by analogy with throughput for movement tasks (TP), a notion of throughput for selection tasks (TPS) was proposed, the mean value for which in the experiment was 5.88, but only 4.8 for elder participants. The appropriateness of TPS concept is somehow supported by its high (.924) correlation with TP, though their mean values are found to be different, and by regression equation for TPS (23) that had relatively high $R^2$=.859 and incorporated factors of subjects' age (T) and low experience (LE). It is also notable that in regressions built for TP and TPS the coefficients for these factors had quite similar values, -.05 for T and -1 for LE.

## 5. References


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