Lecture 6 Human Performance Modeling - 4

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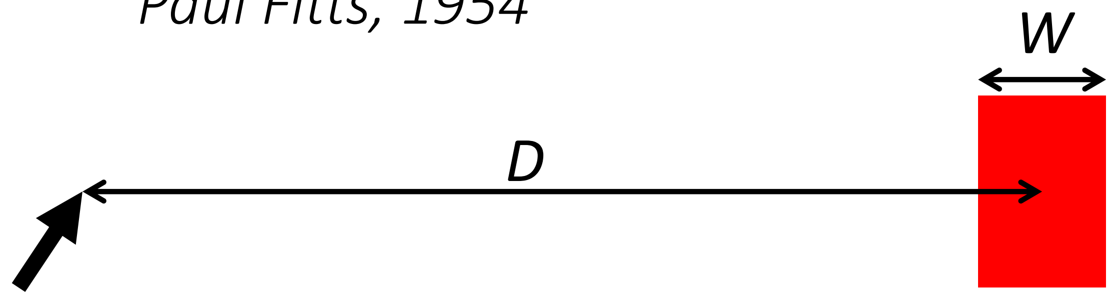
Fitts' Law

Paul Fitts, 1954



$$\underbrace{MT}_{\textbf{Movement Time}} = a + b\underbrace{\log_2\left(\frac{D}{W}+1\right)}_{\textbf{Index of Difficulty}\ (\textit{ID [bits]})}$$

Hick's Law

Uncertainty Principle. Decision time T increases with uncertainty about the judgment or decision to be made:

$$T = I_C H,$$

where H is the information-theoretic entropy of the decision and I_C = 150 [0–157] ms/bit. For n equally probable alternatives (called Hick's Law),

$$H = \log_2 (n + 1).$$

For n alternatives with different probabilities p_i of occurrence,

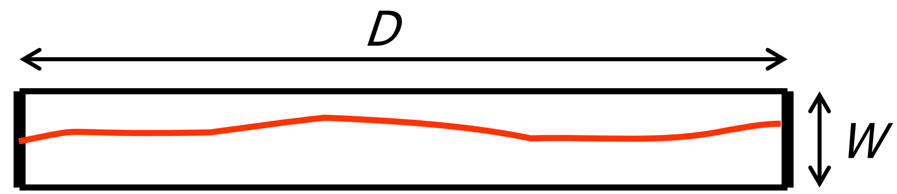
$$H = \Sigma_i p_i \log_2 (1/p_i + 1).$$

Steering Law *(Accot and Zhai, 1997)*

"Beyond Fitts' Law: Models for trajectory based HCI tasks."
Proceedings of ACM CHI 1997 Conference

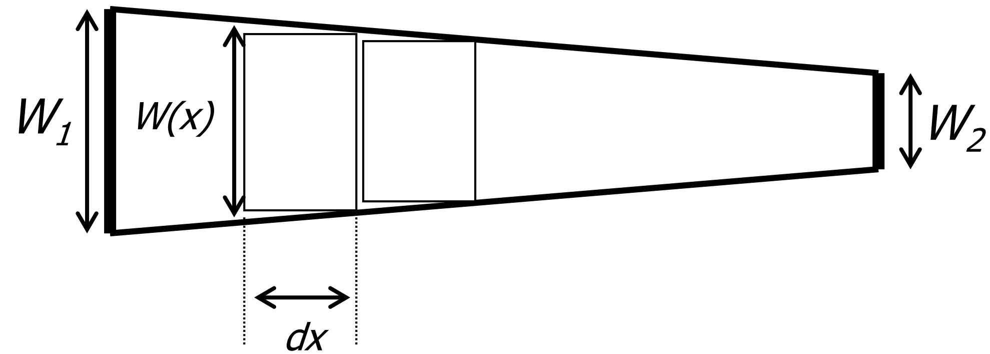
fixed width tunnel:

$$ID = \frac{D}{W}, \quad MT = a + b\frac{D}{W}$$



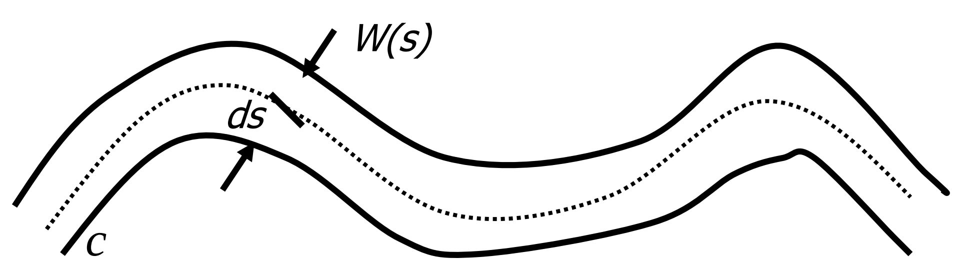
narrowing tunnel:

$$ID = \int_0^D \frac{dx}{W(x)}$$



general Steering Law:

$$ID = \int_c \frac{ds}{W(s)}$$

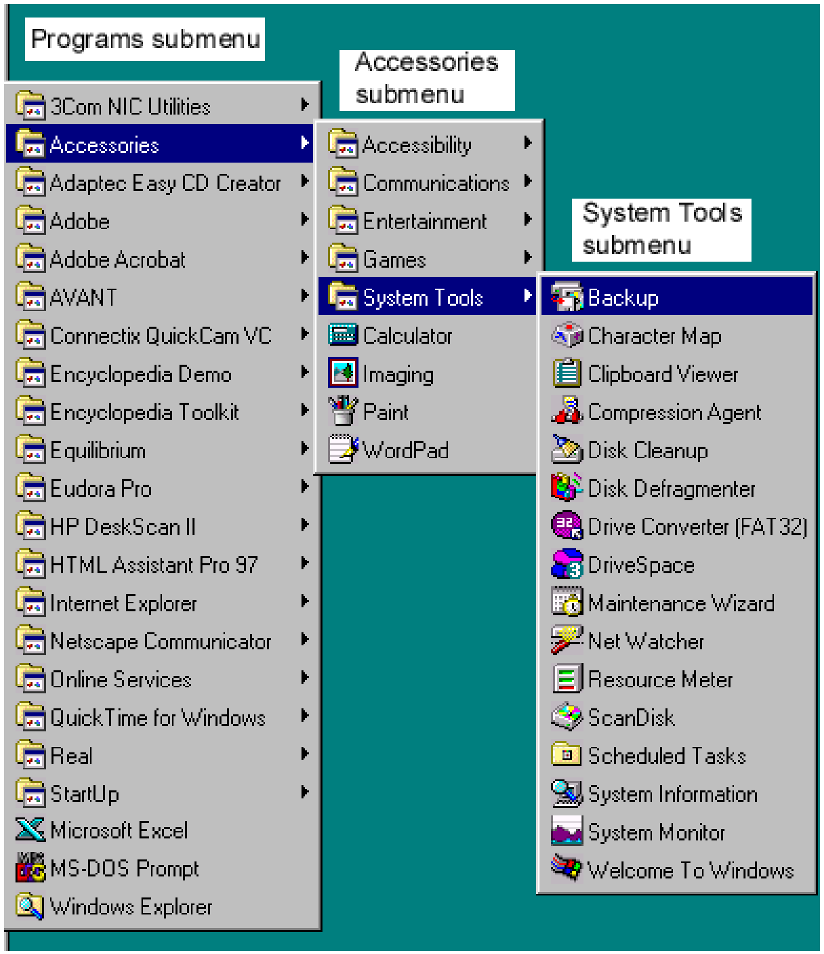


GOMS

- A family of user interface modeling techniques

- Goals, Operators, Methods, and Selection rules
  - Input: detailed description of UI and task(s)
  - Output: various qualitative and quantitative measures

Example: Modeling Menu Performance

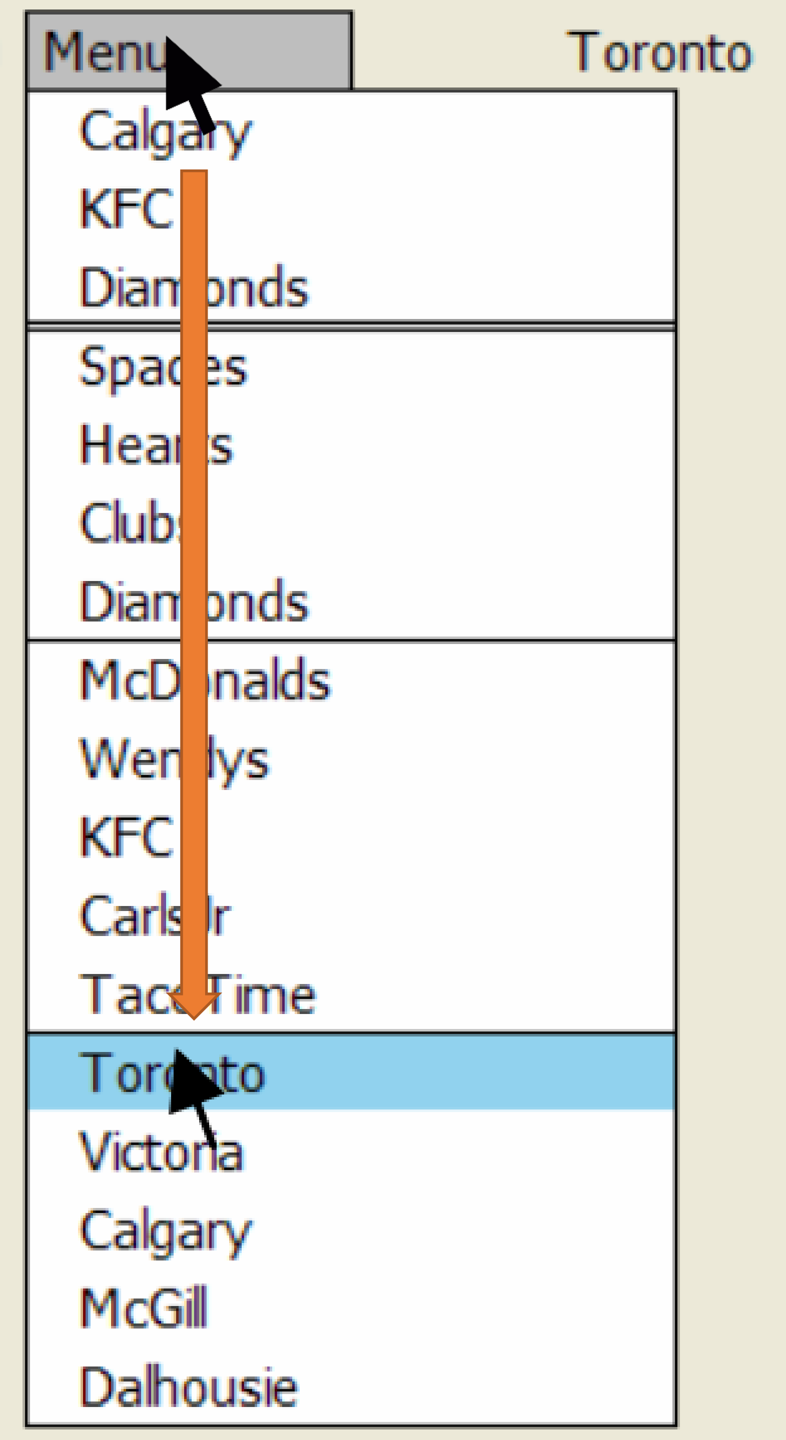


Andy Cockburn, Carl Gutwin, and Saul Greenberg. 2007. A predictive model of menu performance. In *CHI '07*. ACM, New York, NY, USA, 627-636.

How to perform modeling research?

- Propose a model
- Calibration
- Evaluation

What happens when selecting from menus?



- Search the item
- Move the cursor

- Decision/search time
- Movement Time

Learning: Transition from novice to expert

Slide adapted from Wenzhe Cui

Movement Time - Fitts' Law

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

$$MT = a + b \times ID$$

MT - The movement time
ID - index of difficulty, and *A* is the amplitude of movement and *W* is the target width
a, b are constant which we can get from experiment.

Small, distant targets take longer to acquire.

Decision/Search Time - Hick-Hyman Law

$$T_{hh} = a + b \times H$$

$$H = \log_2(1/p)$$

$$T_{hh} = a + b \times \log_2(C)$$

p is the probability of the event
H - information content, likely events have low information content; unlikely ones, high
When the user chooses between C equally probable alternatives, the Hick-Hyman Law can be rewritten as $T = a + b \times \log_2(C)$

The Hick-Hyman Law describes human decision time as a function of the information content conveyed by a visual stimulus

Item probabilities

$$H_i = log_2(1/p_i)$$

$$T_{hhi} = b_{hh} H_i + a_{hh}$$

$$\forall i,\ p_i = t_i / t_t$$

all items are initially equally probable ($\forall i$, $p_i = 1/n$), but that their probabilities are continually modified to reflect the number of times each item is selected ($\forall i$, $p_i = t_i / t_t$, where t_t is the total number of selections in the menu).

Thus, the model can reflect Zipfian or other frequency distributions.

Hick-Hyman is not good enough for search time if we are not familiar with the menu

Visual Search + Hick-Hyman Decision

$$T_{dsi} = (1 - e_i)T_{vsi} + e_i T_{hhi}$$

decision/search time (T_{dsi})
linear visual search-time component (T_{vsi}) (novice)
logarithmic Hick-Hyman decision time (T_{hhi}) (expert)

e_i is the user's expertise with that item, from 0 (complete novice) to 1 (complete expert)

Visual Search Time

$$T_{vsi} = b_{vs}n + a_{vs}$$

We assume that when the user is inexperienced, the visual search time for each item is linear with the total number of items n, and
that the search time is negligible when the user is expert.

Expertise model

$$e_i = L \times (1 - 1/t_i)$$

e_i - user's expertise with menu item i, range from 0 to 1 (novice - expert)
t_i - the number of previous trials (selections) of the item
L - the 'learnability' of the interface

L range 0 to 1, with 1 representing an entirely learnable menu representation that is, the items do not change locations or positions.

The value of L can be estimated for different interfaces by calculating one minus the average distance that items move as a proportion of half of the total menu
length – e.g., random items will on average move half of the menu length l per selection, hence $L=1-0.5l/0.5l=0$

New Model of Model Performance

$$T_i = T_{dsi} + T_{pi}$$

Predicts selection time T_i for each item i, based on the sum of the decision/search time T_{dsi} and the Fitts' Law pointing time T_{pi} for that item

$$T_{pi} = a + b \log_2 (A_i / W_i + 1)$$

$$T_{dsi} = (1 - e_i) T_{vsi} + e_i T_{hhi}$$

$$e_i = L \times (1 - 1/t_i)$$

$$T_{vsi} = b_{vs} n + a_{vs}$$

$$T_{hhi} = b_{hh} H_i + a_{hh}$$

$$H_i = \log_2(1/p_i)$$

$$\forall i,\ p_i = t_i / t_t$$

New Model of Model Performance

$$T_{avg} = \sum_{i=1}^{n} p_i T_i$$

As we are ultimately interested in predicting the average performance of entire menu widgets, rather than just individual selections, we generalize the model to average performance (T_{avg})

For more complex model

Modeling split menus

$$T_i = splitDecision + p_{i\_split}T_{i\_split} + (1 - p_{i\_split})T_{i\_reg}$$

$$splitDecision = (1 - e_{split})T_{hh2}$$

e_{split} is the user's expertise with the contents of the split region of the menu.

splitDecision term models the time required for the user to decide between the split region of the menu and the regular region.

T_{hh2} is the time to decide between the two regions, calculated from $b_{hh}+a_{hh.}$

Calibrate the Model

What to do

- Fitts' a and b
- visual search a_{vs} and b_{vs}
- Hick-Hyman a_{hh} and b_{hh}

$$T_{pi} = a + b \log_2 (A_i / W_i + 1)$$

$$T_{dsi} = (1 - e_i) T_{vsi} + e_i T_{hhi}$$

$$e_i = L \times (1 - 1/t_i)$$

$$T_{vsi} = b_{vs} n + a_{vs}$$

$$T_{hhi} = b_{hh} H_i + a_{hh}$$

$$H_i = \log_2 (1/p_i)$$

$$\forall i,\ p_i = t_i / t_t$$

Method

- Initially completed a Fitts' Law block of tasks involving pointing to cued menu items to calibrate the Fitts' Law parameters *a* and *b*
- Decision/search time (T_{dsi}) by subtracting pointing time from the overall acquisition time $T_i = T_{dsi} + T_{pi}$
- Then completed a series of menu selections in twelve different conditions covering 3 menu conditions (static+unfamiliar, static+familiar, and random menus) and four menu lengths (2, 4, 8 and 12 items)

Method

- Static + unfamiliar
  - 177 countries
  - Inspect the learning Model Accuracy
- Static + familiar
  - Windows Office menu
  - Hick-Hyman a_{hh} and b_{hh}
- Random
  - 177 countries random
  - $T_{vsi} = b_{vs}n + a_{vs}$

Result

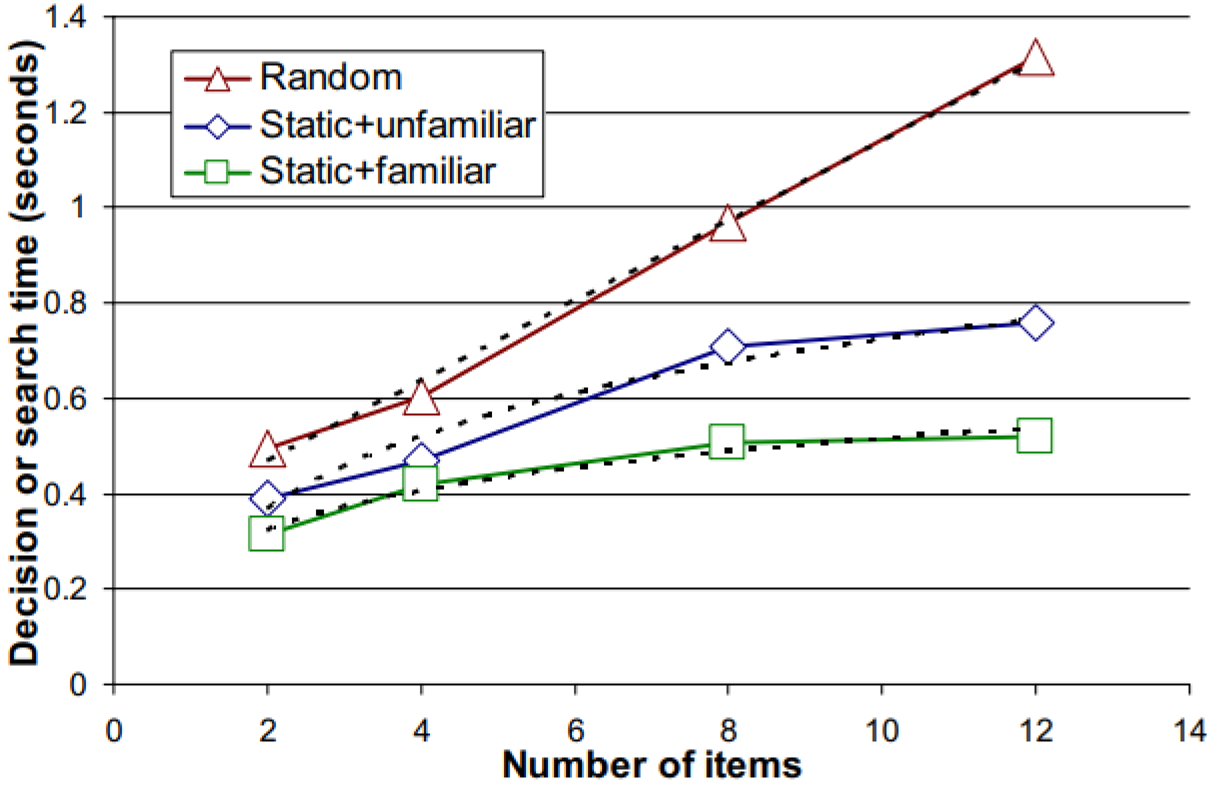


Figure 1 Mean decision/search time (T_{dsi}) for the three menu conditions. Dashed lines show regression models: linear for random; logarithmic for static+familiar and static+unfamiliar.

Result

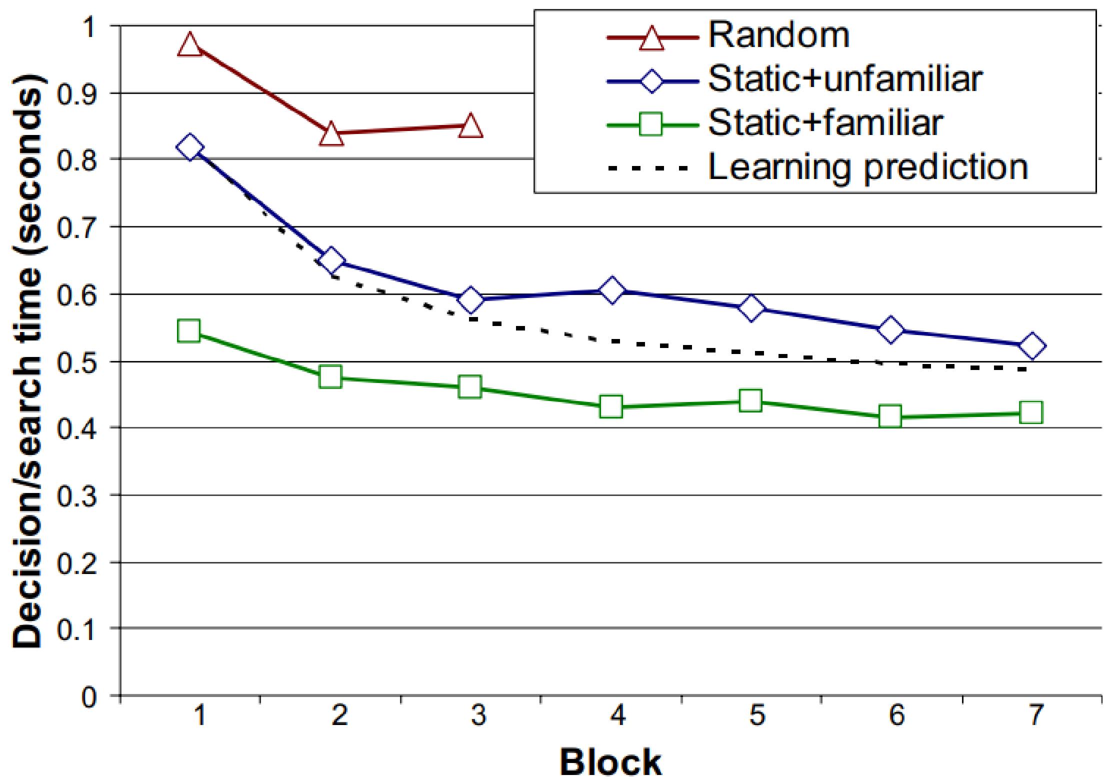


Figure 2. Mean decision/search time for the three menu conditions across blocks of trials (based on the mean of all menu lengths per block).

Result

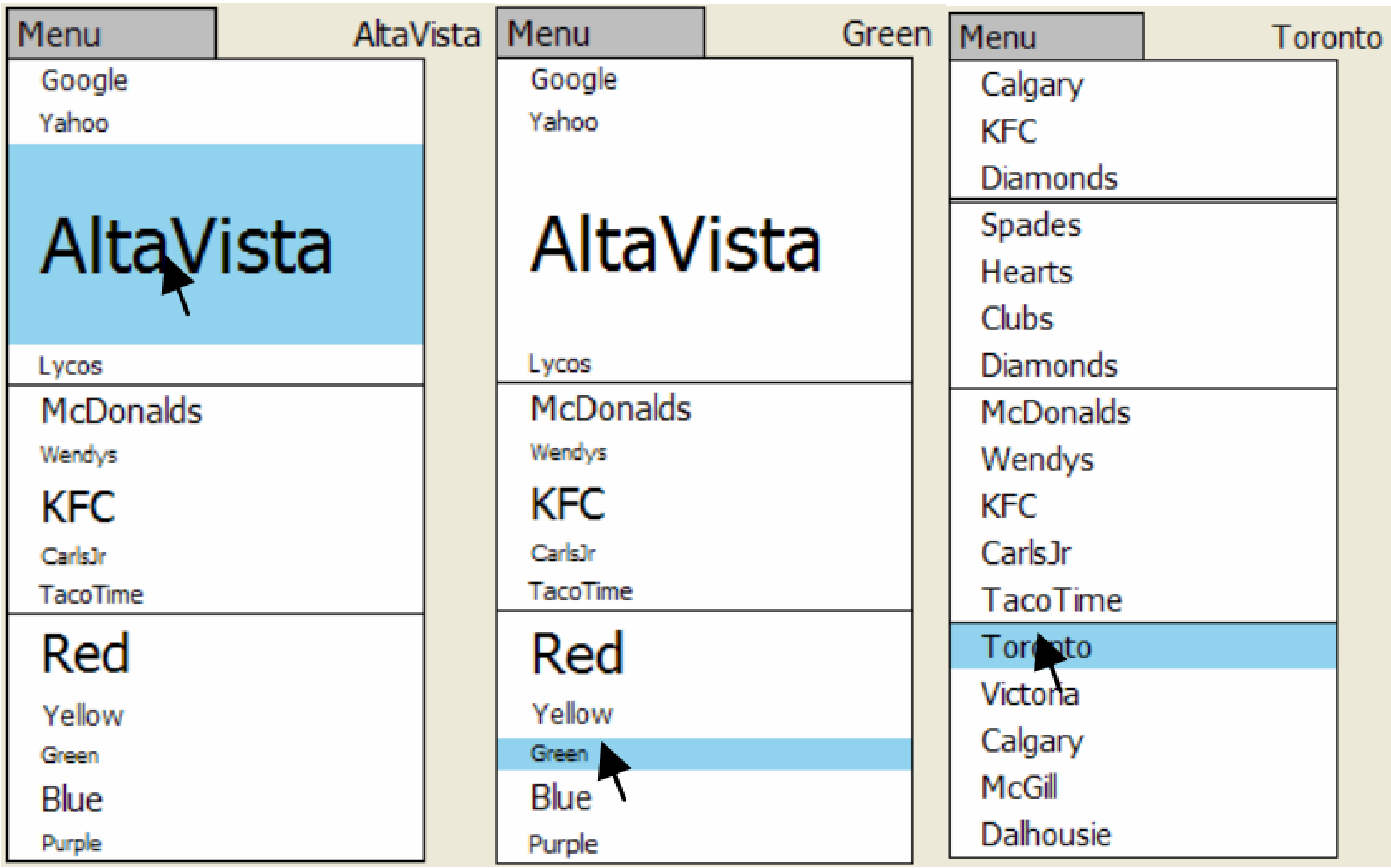
Fitts $T_p=0.37+0.13ID$ (a=0.37s, b=0.13sec/bit)

Novice $T_{dsi}=T_{vsi}=0.08n+0.3$, $R^2=0.99$

Expert $T_{dsi}=T_{hhi}=0.08\log_2(n)+0.24$, $R^2=0.98$

Evaluating the Model

Method



(a) Morphing (b) Morphing (c) Split

Figure 3. Morphing and split menus. The target is shown next to the menu button when posted.

Result

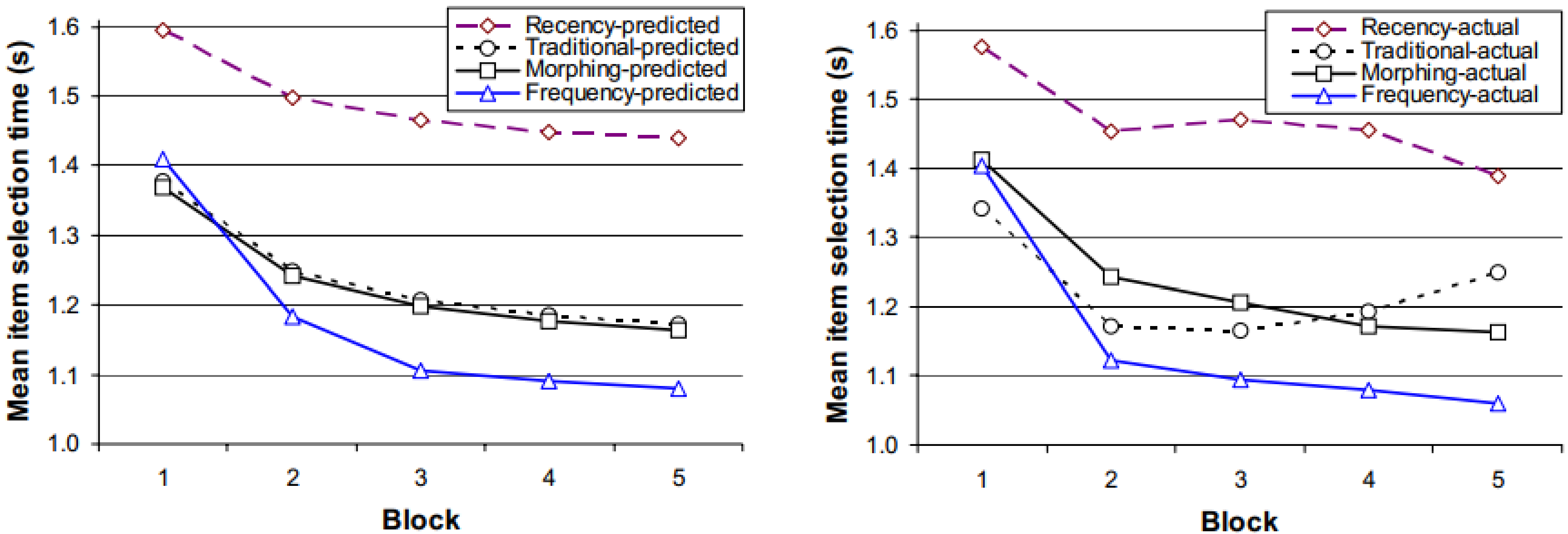


Figure 4. Predicted performance (left) and actual performance (right) (note the baseline at 1.0s).

Empirical data (Figure 4, right) matched the predictions extremely well.