Unified Modeling of Proactive Interference and Memorization Effort: A new mathematical perspective within ACT-R theory

Arindam Das, Wolfgang Stuerzlinger
Computer Science and Engineering, York University, Toronto, Canada
{arindam, wolfgang} @cse.yorku.ca

Abstract

We parsimoniously model the effect of proactive interference and memorization effort in learning stable graphical layouts. We model the visual search cost, i.e. the number of distractors visually encoded while looking for a target item, as a reasonable surrogate of onscreen proactive interference. Further, we show that a novel quantity that we term "effort factor" is an acceptable estimate for comparing the memorization effort across different access cost of onscreen information during the early stages of practice.

Keywords: ACT-R declarative memory, Proactive Interference, Memorization Effort, User Interface

Introduction

Onscreen information is an important part of daily life today – On one hand, they are prevalent in handheld devices like smart-phones and tablets; On the other hand, they can also be found in critical displays in aircraft and other machinery. The screens usually display a structured set of items for the user to interact with. When interacting, it is rare that users remember the position of every item in the set perfectly. One explanation for this forgetting effect is proactive interference caused by distractor items seen during the visual search for the desired item. Proactive interference causes loss of memory activation. In contrast, explicit memorization of item locations helps to mitigate the effect of such interference. People exert mental effort in order to accomplish such memorization.

A study in flight simulation training (Waldron et al., 2008) found that temporarily decreasing the availability of onscreen information for pilots orients pilots more towards memory-based interaction strategies. This in turn helps them better remember critical information such as the aircrafts' location. The study established that an increase in information access cost increases the perceptual-motor effort. This normally encourages users to choose the highest performance option of using fewer perceptual-motor operations but more memory operations, even if memory retrieval is imperfect.

Rowe et al. (2008) empirically suggested that "practice" and "memorization" positively influence visuo-spatial learning while "proactive interference" impacts it negatively. On the other hand, Altmann et al. (2002) proposed a theory that not only holds proactive interference but also "decay" (i.e. loss of memory activation with passage of time) responsible for forgetting. Taking into account the mutually constraining effects of "practice", "memorization" effort, "decay" and "proactive interference", an integrated, yet simple and easily applicable performance model is possible that would reflect the effect of these phenomena on visuo-spatial learning.

Following this idea, we propose a simple mathematical model of visuo-spatial learning that combines the effect of "practice" in terms of *practice time*, the effect of "decay" in terms of a small *numeric constant*, the effect of "proactive interference" in terms of *visual search cost*, and the effect of "memorization" effort in terms of a newly introduced model parameter, an *effort factor*, explained later. All these effects are expressed in a single equation of memory activation. To achieve this goal, we adapt an existing memory activation equation of ACT-R theory developed by Anderson et al. (1998). We focus on the cognitive aspects of interaction more than the perceptual-motor control complexities in our model. Therefore, we leverage the empirically proven axioms of ACT-R theory that the time cost of a visual encoding is a constant and that a motor response can be modeled as an average value, according to the task specific behavior, such as a mouse movement.

Guided by Altmann et al. (2002), we implement our mathematical model in a spreadsheet and validate it against previous empirical data collected by others.

ACT-R Theory of Declarative Memory

The ACT-R theory by Anderson et al. (1998) describes a modular system that aims to replicate the human mind. The theory is a framework of mathematical equations that models the neural computations in order to realize human dynamic behavior.

The core of ACT-R declarative memory builds upon the notion of memory activation. It posits that memory encodings of items have different levels of activation to reflect their past use: items that have been used recently or items that are used very often receive a high activation. This activation decays over time if the item is not used. When the cognitive system needs to retrieve an item, memory returns the one with the highest activation at that instant. The job of memory retrieval is complicated by the noise in activation levels, which can temporarily make an item more active than the current one, or which can temporarily push all items below a threshold, thereby making the cognitive system transiently unable to recall information (Altmann et al., 2008; p. 604). Furthermore, the activation of an item controls its speed of retrieval. We focus on the following three equations behind the ACT-R declarative memory system that we leverage in our current work.

ACT-R Activation Equation

The equation describing the activation, A, of an item in the memory is given by

$$A = B + \varepsilon \qquad \textbf{Activation Equation} \qquad (1)$$

where B is the base-level activation of the item discussed later in detail and ε is the noise component. Noise is assumed to cause transient fluctuations in activation levels. Guided by Altmann et al. (2002), we implement the noise ε as a constant for our modeling purposes. In the complete ACT-R memory model, environmental context and relevance to the current goal also influences the activation of an item (Gray et al., 2006, p. 481). However this component introduces additional complexity not relevant to our modeling effort in this work. Being guided by Gray et al. (2006) we have therefore omitted the component here.

ACT-R Base-Level Activation Equation

The equation describing the base-level activation of an item in memory is given by

$$B = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right) \quad \textbf{Base-Level Activation Equation} \quad \textbf{(2)}$$

where n is the number of "practices" of the item completed so far, t_j is the age of the j-th practice of the item, and the negative exponent d is the decay constant that controls how quickly the activation decreases. As postulated by ACT-R theory, the d term thus models the loss of memory strength with the passage of time. The equation therefore represents the strength of a memory item as the sum of a number of individual memory strengthening, each corresponding to a past practice event. It implies that each time an item is practiced, the activation of the item receives an increment in strength that decays away as a power function of time.

ACT-R Reaction Time Equation

The activation of an item discussed earlier controls its speed of retrieval. The time required for the declarative memory to respond to a request (recognition or recall) for an item is given by the following equation:

$$RT = I + F * e^{(-f * A)} \quad \textbf{Reaction Time Equation} \quad \textbf{(3)}$$

where I is an intercept time reflecting the time cost of perceptual (visual) encoding and motor response. F is the latency factor, and maps activation to time. f is the latency exponent. The purpose of parameters F and f is only to scale the time to retrieve an item from memory. They remain fixed across all experimental conditions.

The time cost of a visual encoding is set at 185 ms which is taken from the estimate used by ACT-R (Anderson & Lebiere, 1998, pp. 150–151) for human attention to move to an object at a location.

The time cost of a motor response is set according to the task specific behavior. The task we model involves finding a pre-cued item on a structured layout of graphical buttons presented on a computer screen and then selecting it by clicking on the appropriate button using a mouse (Ehret, 2000, 2002). Guided by Ehret (2000), Gray et al. (2006) and Card et al. (1978), we estimate the average time cost of a motor response to be 300 ms for our modeling purposes.

The Model

We next propose our extension to the base-level activation equation in order to account for the effect of proactive interference and memorization effort. We do so largely by adapting existing cognitive constructs rather than developing entirely new ones.

Proactive Interference Modeling

Our approach adapts ACT-R's classic model of memory strength to account for proactive interference. In other words, we account for the effects of distractors that get visually encoded or cumulated before the encoding or accumulation of the target item, during a visual search. We accomplish this by replacing the decay constant, d, of the base-level activation equation, with a function consisting of a constant term and a varying term. The constant term models the loss of memory strength with passage of time as before. The new varying term models the loss of memory strength due to proactive interference. Our proposal for modeling the combined effect of decay and interference on memory activation is in line with the observations of Altmann et al. (2002, 2008) which indict both decay and proactive interference for forgetting.

The varying term we propose is governed by the visual search cost – the number of distractors that get visually encoded prior to encoding the target item when one tries to find an item on a user interface. The encoded number of distractors during a search contributes to a measure for the proactive interference effect: The lower the number of distractors visually encoded during a search for a target item, the lower should be the "loss" of activation of the target item. Hence, the next recall of that item will be affected by its higher activation, leading to the lowering of its retrieval time. This will show an improvement in "search and selection" performance time during exploration of the interface. Our hypothesis is grounded in the primary research result of Underwood (1957) on proactive interference, namely, the effect that the number of previously learned items has on the recall of the target item: The lower the number of previously learned items is, the lower is the forgetting effect and therefore the lower is the recall latency for the target item.

We propose a decay rate, d_j, calculated for an item, after j practices of the item are completed, as follows:

$$d_j = h + 0.5 * X_{j-1}/N \quad \textbf{Decay Rate Equation} \quad \textbf{(4)}$$

where h represents the time-based decay constant, the fraction 0.5 is a scaling factor (our choice of 0.5 is explained in the next paragraph), N is the total number of items on the layout and X_{j-1} is the number of distractors visually encoded at the time of j^{th} practice. Naturally, j has to be larger or equal to 1. X_0 denotes the number of distractors encoded at the first practice. When X_{j-1} is 0, i.e. when the user is able to complete the task by direct recall, without going through any explicit visual search, the decay rate equation degenerates to $d_j = h$. This implies that, in the absence of the impact of distractors, decay in activation occurs only with the passage of time as modeled by the classic base-level activation equation.

We introduce the varying term $0.5*X_{j-1}/N$ to represent the loss of memory activation due to proactive interference. It transforms the number of distractors, X_{j-1}, to a "decay" value suitable for ACT-R theory. We assume such values to be ranging from 0 to 0.5: Since 0 implies no decay, it can be considered as a lower bound. The value of 0.5 is used as the default decay constant in the classic ACT-R theory (see Anderson et al., 1998). Therefore 0.5 can be considered as a valid upper bound for our work. The ratio X_{j-1}/N ranges from 0 to 1. Consequently, the varying term $0.5*X_{j-1}/N$ results in a value in the desired interval, 0 to 0.5. The $0.5*X_{j-1}/N = 0.5$ refers to a situation where the maximum possible number of distractors is encountered, i.e. when $X_{j-1} = N$, leading to the highest level of proactive interference effect. This, in turn, reduces the term to the maximum of 0.5. On the other hand, $0.5*X_{j-1}/N = 0$ implies an absence of impact from distractors, and therefore no proactive interference effect as a consequence. This occurs when the user is able to complete the task by direct recall.

Our model of proactive interference is adapted from the model of Das et al. (2010). Our work is a significant improvement over their model of proactive interference because firstly, our decay rate equation contains less number of free parameters (decay constant h is the only free parameter in our equation) and secondly, our equation is constrained by the total number of items, N, of a layout under scrutiny. Consequently, the chances for data overfitting decrease significantly in our model.

Memorization Effort Modeling

Our modeling of memorization effort is guided by the *soft constraints hypothesis* of Gray et al. (2006). The soft constraints hypothesis is a rational analysis approach which proposes that the mixture of perceptual-motor and cognitive resources allocated for interactive behavior is adjusted based on temporal cost-benefit tradeoffs, such that the least-effort path of executing the visuo-spatial task at hand, gets implicitly chosen. As perceptual-motor effort increases, users will normally choose the least-effort option of fewer perceptual-motor operations and more memory operations, even if the memory retrieval is imperfect. We term the effort exhausted in carrying out the memory operations as "memorization effort".

The soft constraints hypothesis concludes that the tradeoff between selecting the perceptual-motor versus cognitive behavior minimizes the total effort (and hence performance cost) measured in the currency of time (Gray et al., 2006, p. 463). Motivated by the hypothesis, we introduce a parameter in the base-level activation equation of ACT-R (Equation 2) as a coefficient of practice time and include it inside the logarithmic term (shown later in Modified Base-Level Activation Equation). We call this novel parameter *effort factor*. We hypothesize the effort factor to be the "temporal" representation of the memorization effort expended to accomplish a visuo-spatial learning task. The works of Anderson (1983, p. 277) as well as Stewart et al. (2007, p. 235), also motivate our choice for the adoption of an effort factor, as they suggested the usage of a cost factor similar to ours, albeit in different domains.

Modified Base-Level Activation Equation

With the decay rate equation and the effort factor parameter conceptualized, we modify the base-level activation equation (Equation 2) to

$$B = \ln\left(k\sum_{j=1}^{n} t_j^{-d_j}\right)$$

Modified Base-Level Activation Equation (5)

Equation 5 is obtained by adding two new elements d_j and k to Equation 2. We explain the new elements below.

d_j describes the new *decay rate equation* (Equation 4) that sums up two terms: one representing the traditional time-based "decay" constant and the other representing the "loss of activation due to proactive interference".

The element k is the aforementioned *effort factor* parameter. We explain k in the context of learning layouts that vary in the information access costs (henceforth referred to as "access cost") associated with their items. The access cost differs in terms of representativeness of item labels. Our context of learning accounts for the fact that the total practice time for learning is held constant across all layouts (i.e. for every level of access cost).

If all model parameters, except k, in Equations 1, 3, 4 and 5 are left at fixed values across layouts that differ in access costs, then we hypothesize two properties about k while comparing layouts in terms of reaction time estimates (*RT*) of Equation 3 as follows:

(i) First, we hypothesize that one value of k corresponds to one particular layout, i.e. one particular access cost condition.

(ii) Second, a lower value of k would correspond to higher memorization effort whereas a higher value of k would correspond to lower memorization effort. The Appendix provides an argument for this.

Our modified base-level activation equation is therefore a hypothesis that accounts for the combined effect of "practice time", "memorization" effort, "proactive interference" and "decay" on visuo-spatial learning performance. We validate our hypotheses later in this work.

Our model of memorization effort is adapted from the work of Das et al. (2012). Their model did not account for proactive interference which is the central constraint compared to decay in learning in situations where learning is affected by distractors (Altmann et al., 2002, 2008). Moreover, they had varied the values of multiple model parameters across different conditions of access cost leaving their model vulnerable to overfitting.

Validation

In order to validate our model, we use existing experimentally derived data sets for human performance over several practice sessions for location learning of items in a stable layout. Our goal is to focus on the novice to expert transition because of two reasons. On one hand, the effect of proactive interference is most pronounced during this transition phase. On the other hand, the effect of memorization effort to overcome such interference is also evident in this stage. We therefore concentrate on modeling early sessions of skill development. Each data set we validate against corresponds to a certain access cost in terms of label representativeness of graphical buttons that were laid out on a computer screen. The task we model involves finding a pre-cued button and selecting it using a mouse.

We next explain the rationale behind all model parameter values that were fixed across all experimental conditions.

The time-based "decay" constant h in the decay rate equation was fixed at $h = 0.058$. We are motivated here by Pavlik et al. (2005, p. 572), who used it as a decay intercept albeit in a different modeling context. In the absence of any inter-trial data in the empirical study that we validate against, we assume that there have been insignificant pauses between any two consecutive trials. Hence, a relatively small value for the time-based "decay" constant is appropriate, implying that the decay due to passage of time had been minimal. Since the focus of our decay rate equation is to model the effect of proactive interference, we place greater emphasis on the role of distracting information. In this regard, we are motivated by the discourse of Altmann et al. (2002) who argues for the influential role of proactive interference in forgetting compared to the role of decay in the domain of distractor-affected learning. Our choice of a very small value of the time-based "decay" constant is therefore appropriate.

The activation noise ε in the activation equation was fixed at $\varepsilon = 0.28$, a value in line with other applications of this equation in the domain of graphical user interface (e.g., Gray et al., 2006).

The latency factor F in the reaction time equation is left at its default value of $F = 1$sec, as per classic ACT-R theory.

The latency exponent f in the reaction time equation is fixed at $f = 0.65$. On carrying out sensitivity analysis, we found that setting f at 0.65 instead of 1 substantially reduces the root-mean-square error (RMSE) value between the human data and its corresponding model data. It has very negligible influence on the correlation between them.

As we discuss below, the effort factor k of the Modified Base-Level Activation Equation is the only parameter that we varied across conditions in order to account for the relative differences in memorization effort spent in learning layouts with different access costs (conditions).

Circle of Buttons Experiment

Knowing an object's location can reduce a user's task time, errors, and frustration. As the number of screen objects increases, so does the utility of location knowledge. Ehret (2002) carried out an experiment that tests how well users learn the location of buttons arranged in a circle on a computer screen and how the mechanisms underlying location learning interact with the level of meaningfulness of button labels. He used a "search and select" task in which, for a given trial, participants were presented a particular color and were required to find and click the button associated with that color. The correct button was one among the twelve buttons that remained in constant positions throughout the experiment. The contour and shape of every button was always visible across all conditions (Ehret, 2000; Figure 2, p. 27). To discourage errors, when participants clicked the wrong button the computer would beep five times, a dialog box would appear, and the trial would have to be repeated (Ehret, 2002; p. 212).

Ehret's observations were point-of-gaze data collected via an eye-tracker. In order to validate our model we extracted three data sets from his observations. The data sets were mean "visual search and select" time (reaction time) from an experiment, limited to the first 10 sessions of practice, since learning plateaued off after the tenth session. In his study, Ehret (2002; 2000, p. 19) had reported two costs, the visual search cost which is the number of buttons visually encoded before the target button is found and the verification time, which is the time required to decide whether the button visually encoded is really the target or not. For a given session, we arrived at the mean human *reaction time* per button by multiplying the mean visual search cost with the mean verification time corresponding to that session.

The three data sets differed in the level of meaningfulness of labels associated with the buttons. The first set of data was obtained while searching for a pre-cued color in buttons labeled with the name of color written in English. The aim was to have a meaningful association between a color and the button representing the color. The second set of data was obtained while searching for buttons labeled with arbitrary icons. The aim was to reduce the meaningfulness of the association between a color and the button representing it. The third set consisted of the reaction times for searching and selecting a pre-cued color among buttons with no labels on them. The aim was to eliminate any meaningfulness of the association between a color and the button representing it. The data sets thus contain three sets of *reaction times* corresponding to the three different levels of difficulty in accessing information: *textual* label, *arbitrary* label and *invisible* label. Each condition therefore represented a certain level of access cost, the *textual* label condition being the lowest cost condition among them. *The total practice time was held constant across all conditions*. It is to be noted that for the arbitrary and invisible label conditions, a tooltip was provided for each button to aid the subject, if memory failed. Accessing the tooltip for a button revealed a small rectangle containing the color associated with it. The cost of accessing this tip was a one-second delay between moving the mouse cursor to the button and the appearance of the tooltip.

Our choice of data aligns with our modeling objective. We aim to model the combined effect of *visual search cost* (the surrogate of proactive interference) as well as *memorization effort* on reaction time, over a reasonable number of practice sessions. Ehret's data shows that for any given access cost condition, the visual search cost decreases over practice sessions implying that proactive interference decreases with practice. However, Ehret's data further shows that during the search for a pre-cued color, as the access cost increased from *textual* to *arbitrary* to *invisible* label conditions of buttons, so did the time to visually verify and decide (verification time) whether a button currently under scrutiny is indeed the target or not, at any given session. The verification time was observed to be the lowest for the textual label condition and highest for the invisible label condition. In other words, the layouts with higher access cost featured higher verification time to identify the correct item, implying higher effort to learn those layouts compared to the ones with lower access cost. As posited by the soft constraint hypothesis and given the same amount of practice time across all conditions, the higher perceptual cost of arbitrary and invisible label conditions results in a higher memorization effort for those label conditions compared to the memorization effort required for the textual label condition.

For our validation, we had to make a few assumptions, as certain information was not mentioned explicitly in the work of Ehret (2002). The assumptions are the same across all conditions as follows: Each practice session took 37.5 seconds to complete – since 16 sessions took 10 minutes or 600 seconds as expressed in a related work by Ehret (2000, p. 136). We also assume the inter-session periods to be constant. Also, except for the target pre-cue, we assume that environmental context cuing is minimal and irrelevant for our purposes.

Validating the Proactive Interference Effect

We provide an example scenario on how the effect of proactive interference on spatial learning can be modeled using our new model. Ehret (2002) had an onscreen layout of graphical buttons labeled with icons where each icon is arbitrarily associated with a color. A subject's task was to visually search for a pre-cued color among the buttons and click the appropriate button when found using a mouse. The pre-cued color always appeared at the center of the circle. In case the subject's memory failed to recall the color associated with a button, she could access the button's tooltip to know its color by moving the mouse cursor over it. The tooltip appeared after a one-second delay once the mouse cursor was moved to the button.

The mean numbers of distractors measured in Ehret's experiment in the *arbitrary* label condition are 5.27, 2.93, 2.58, 2.34, 2.31, 1.61, 1.49, 1.31, 1.36 and 1.14 corresponding to sessions 1 to 10. We input these numbers in the decay rate equation of our model to obtain the mean activation value per item for each session. We adjust the value of k in our model to 0.068 for the experimental condition (i.e. arbitrary labeling condition). The other model parameters stay fixed at the values discussed earlier. We fit our model to the empirical reaction time for a button. We found the R^2 of the fit to be .993 implying a qualitative correspondence between human and model results.

The effect of proactive interference was also evident in the *textual* label condition. After substituting the values of mean numbers of distractors for this condition (measured in Ehret's experiment) in the decay rate equation, we again found a close match between the human and model results with $R^2 = 0.978$. Our adjusted value of k was 0.500 in this condition.

As apparent from the decay rate equation, a change in the number of distractors changes the decay rate. While modeling the proactive interference, we noticed that the mean number of distractors per item, X_{j-1} in the decay rate equation influences the shape of the curve at each session-point. A small change in the decay rate, d_j, (at the level of 10^{-2}) is found to have noticeable impact on the reaction time estimates. This is particularly true for the first few sessions of practice.

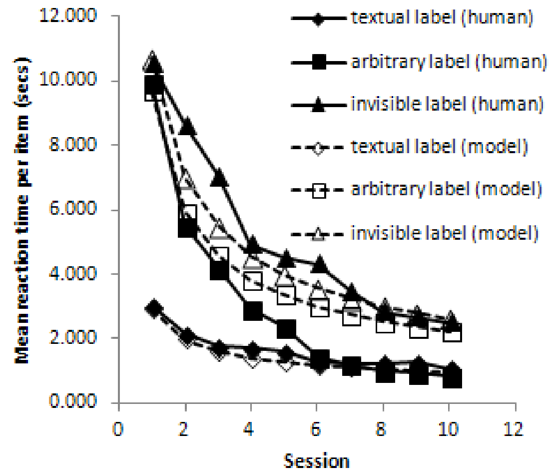

Figure 1. Reaction times per item (button) for *textual*, *arbitrary* and *invisible* label conditions.

Validating the Comparison of Memorization Effort

Figure 1 shows the fit of our model to the human data in terms of reaction times. We compared the effort factor k for the *invisible label* condition against the *textual label* condition. We found $k = 0.056$ for the difficult to access *invisible* labels, compared to $k = 0.500$ for the easily accessible *textual* labels. Furthermore, k was 0.068 for the difficult to access *arbitrary* labels, compared to k being 0.500 for the easy to access *textual* labels. The comparison of k in both instances thus points to lower values of k for layouts with high access cost (high perceptual cost) compared to the conditions where relevant information is easily available in the environment. We therefore conclude that the comparison of memorization effort via our new effort factor k follows the soft constraint hypothesis to a significant extent.

With $R^2 = 0.978$, RMSE = 0.215 for the *textual*, $R^2 = 0.993$, RMSE = 1.153 for the *arbitrary* and $R^2 = 0.941$, RMSE = 0.785 for the *invisible* conditions, the correlation between the human and model data were good. The RMSE as a percentage was 13% for *textual* and 15% for *invisible* condition. However, the percentage RMSE for *arbitrary* condition being 38% was higher than the 20% mark suggested by John and Newell (1989). The RMSE for the *arbitrary* condition therefore implied a high error.

Discussions

Our work in this paper introduces two mathematical terms, one to account for the effect of "proactive interference" (PI) and the other to account for the effect of "memorization effort". We add them to an existing memory activation equation of ACT-R theory that hitherto accounted for the effects of only "practice" and "decay".

In this work, we have left all but one model parameter fixed across all conditions, thereby omitting the scope of overfitting significantly. The effort factor k is the only model parameter that we varied in order to reflect the differences in the memorization effort across different accessibility conditions.

Earlier, Altmann et al. (2002) had used ACT-R theory to mathematically model the effect of PI on recall probability. On the other hand, we have mathematically modeled the effect of PI on response latency.

Our modulation of decay rate to reflect PI is motivated by the approach of previous researchers such as Pavlik et al. (2005), Cochran et al. (2006) who had modulated the decay rate to model phenomena, albeit different from PI.

Previously, Ehret (2000, 2002) had used ACT-R theory to model memorization effort. Unlike ours, his approach involved computer-based simulation. In this work, we provide an alternative look at Ehret's modeling endeavor. We do so through a mathematical model.

Initially, to keep our modeling endeavor simple, we started out by creating separate models of proactive interference as well as memorization effort. While developing the standalone model of proactive interference, we tried to leave the effort factor constant across all conditions. On the other hand, while developing the standalone model of memorization effort, we tried to leave the decay rate constant across all conditions. In both cases, however, we were unable to identify fixed values for model parameters. Rather, every "access cost" condition demanded a separate set of values for multiple model parameters to fit the data in a satisfactory manner. This motivated us to model proactive interference and memorization effort in a *unified* way.

Our mathematical model has its limitations. (i) At any given trial for searching a target location on a layout, when the number of distractors X_{j-1} encountered is much less than the total number of items N on the layout, we assume that proactive interference owing to that trial has been negligible. This situation may arise when N is very large. Further investigation is warranted to identify a practical upper limit on N. (ii) Our model is restricted to comparing layouts that have the same number of items in them. (iii) We do not consider the level of similarity between distractors and target. (iv) Increased recall latency observed in high PI conditions can be caused by interference of the target with distractor activations at the time of retrieval. We have not considered that. (v) ACT-R theory has a threshold parameter that specifies a minimum activation below which an item is invisible to the cognitive system. Similar to Altmann et al. (2002), we assume no such threshold. As the threshold parameter is not a variable in the equations we use, this assumption does not impact our work directly.

Our model concentrated purely on the cognitive aspects of interaction; thus it did not model the motor control complexities involved in the spatial search and selection processes on graphical user interfaces. In reality though, these are all important factors that influence the overall user experience.

The advantages of our proposal are its simplicity and transparency. However, it is an ad hoc alternative focused at solving a specific problem in a specific way. We do not claim that we have arrived at a "generic" solution.

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Appendix

If the effort factor k is varied while leaving other model parameters at fixed values across different accessibility conditions, then a lower value of k would correspond to higher memorization effort whereas a higher value of k would correspond to lower memorization effort. The reason is as follows. A lower k (in Equation 5) results in a higher RT (in Equation 3). Higher values of RTs are typically evident in the early stages of practice for layouts with higher access costs (see the empirical data in Ehret, 2002). However according to the soft constraint hypothesis, learning a layout with higher access cost would require a higher number of memory operations compared to perceptual-motor operations. Consequently, we conclude that a lower value of k refers to a higher number of memory operations and therefore reflects higher memorization effort. In contrast, a higher value of k refers to a lower number of memory operations and therefore reflects lower memorization effort.