Unintended Effects: Varying Icon Spacing Changes Users' Visual Search Strategy

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ABSTRACT

Users of modern GUIs routinely engage in visual searches for various control items, such as buttons and icons. Because this is so ubiquitous, it is important that the visual properties of user interfaces support such searches. The current research is aimed at deepening our understanding of how the visual spacing between icons affects visual search times. We constructed an experiment based on previous icon sets [8] where spacing between icons was systematically manipulated, and for which we had a computational cognitive model that predicted performance. In particular, the model predicted that larger spacing would lead to slower search times. While this prediction was borne out, there was an unanticipated finding: users in this new experiment were substantially slower than in previous similar experiments with smaller spacing. In fact, results from this new experiment were better fit with a model that employed a fundamentally different, and less efficient, search strategy. A second experiment was conducted to explicitly test the surprising result that this varied and larger icon spacing would lead to increased search times. Results were consistent with this hypothesis. These results imply that while small differences in visual layout may not intrinsically produce large differences in user performance, they may cause users to adopt suboptimal strategies that do produce such differences.

Author Keywords

Visual Search, Iconic Displays, User and Cognitive Models

ACM Classification Keywords

H.5.2 [Information Interfaces and Presentation]: User Interfaces--Benchmarking, Theory and methods; H.1.2 [Models and Principles]: User/Machine Systems

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INTRODUCTION

With the advent of graphical user interfaces (GUIs) for computers came the convention of representing computer files, commands, and objects with icons. Icons are so commonly used today that most computer users are dependent on them to issue commands or find files. The task of searching for an icon and its associated file name is one with which computer users have become very familiar. Icons are especially useful in handheld devices such as personal digital assistants and cellular phones. These devices have much smaller screens than typical desktop computers, and hence it is important to conserve available screen space. Icons help alleviate this problem because they can convey more information or represent many commands in a minimum amount of space. Icons may differ in size, shape, color, and motion, whereby, some, none, or all of these aspects can be used to provide information to users. Because iconic representation has become very common, more research examining how people search for icons is needed.

The widespread adoption of icons meant that a memory task (e.g., recalling file names) was replaced with a visual search task (e.g., finding an icon that represents a desired file). In order for a person to use an icon, they must first, of course, be able to locate it. The process of visual search is important because it affects several crucial aspects of target selection: time needed to find the target, whether the target will be correctly identified as such, and whether the target will be found at all. When icons are used, the cost of such file representation must be examined. This cost includes both the time spent completing a task and associated selection errors. Further research could help reduce this cost as better-designed icons could represent a larger volume of information more effectively.

While the cost in user time of "bad" icons may seem small—a second here, a second there—the importance of such small effects becomes more salient in non-desktop applications. As GUIs propagate to places such as automobiles and hospital emergency rooms, small differences in time and/or accuracy of visual search are enormously magnified. Consider the case of on-board displays in automobiles, or mobile phone use while in an automobile. A car traveling at 55 mph moves about 80 feet in one second. Thus, a display which takes one second longer to search is an extra 80 feet where the driver is not watching the road or monitoring the actions of other drivers.

As Byrne [3] has shown, all icons are not equal. Simple icons can act as much better search guides than can complex ones, especially as the number of icons displayed increases. Thus, the quality of an icon can be judged by its distinctiveness and complexity. Fleetwood and Byrne [7, 8] and Fleetwood [6] (from here referred to as F&B) found that different quality icons produce different types of visual search strategies. With high quality icons, people can identify clusters of icons preattentively. People tend to search first within such groups and not conduct a general search using a simple strategy such as a left-to-right search.

Byrne [3] attempted to identify factors that might influence the speed of visual search in mixed text/icon displays, such as displays of files and folders. These include a number of non-visual (e.g., the amount the user knows about the target) as well as visual factors. HCI researchers and/or experimental psychologists have not systematically explored most of the non-visual factors. However, there is a considerable literature on how visual factors such as target size and color affect visual search times in non-icon contexts. Prominent reviews and theories can be found in Treisman and Gelade [16] and Wolfe [18]. In general, as the number of items on a display increases, the time to search the display for a particular item increases in a linear fashion. The critical measure of the quality of a target and distractor set is the slope of that line.

Essentially, what the visual literature has shown is that visual search can be "guided" by certain visual features such as color. When a target can be differentiated from distractors by a single visual feature, it is possible to find the target in constant time regardless of the number of distractors. For example, if the target is green and all the distractors are red, the number of red distractors does not matter, so the search slope is zero. For more complex searches, such as searches of real computer displays, the slope will be nonzero. However, better icon design, informed by knowledge of visual search processes, should yield shallower slopes, as shown in [3,6, 7,8].

F&B took this notion one step further and constructed computational cognitive models to simulate users performing searches of mixed icon/text displays. These models used ACT-R 5.0, a cognitive architecture for simulating and understanding human cognition that combines a model of cognition with perceptual-motor capabilities [1, 4]. In the final F&B model, ACT-R uses a visual feature of the target to locate potentially matching icons, but directs attention to the label and does not attend directly to those icons during search. Visual attention is only directed to the icon itself after the target has been identified, as participants must attend to the icon to be able to click on it. Once the model determined that the label on which attention was focused was not the target, it looked for the one nearest to the current icon that has the same features as the target icon. Using this model, F&B were able to obtain predictions that closely matched their experimental data ($R^2 = 0.98$, mean absolute error = 3.19%).

This model is obviously highly dependent on ACT-R's visual system, which is a feature-based attentional system that includes EMMA. EMMA is an eye-movement model that integrates eye movements, visual attention, and cognitive processes [11]. EMMA uses the following equation to predict the time T_{enc} needed to encode an object i:

$$T_{enc} = K \bullet [-\log f_i] \bullet e^{k\varepsilon_i}$$

where f_i is the frequency of the object represented with a probability between 0 and 1; ε_i is the eccentricity of the object, measured in units of visual angle as the distance between the current eye position and the object; and K and k are constants [11].

This is relevant because the F&B model, based on the EMMA equation above, predicts that the spacing between objects should affect how rapidly they can be searched. This model predicts that smaller spacing should yield shorter search times, because wider spacing will cause longer encoding time for individual visual objects.

Experimental results relevant to this prediction have been mixed. Counter to this prediction, increasing the screen density (the proportion of the screen displaying information) has been shown to increase search times in some laboratory studies [5,14,15]. In Cohen and Ivry's study [5], search times for a conjunctively defined target were longer when the space between distractors was smaller. They proposed that this occurred because there are two feature integration mechanisms that operate at different speeds. The fast mechanism codes an object's coarse location information with the initial registration of its visual features. This mechanism cannot operate when objects are located close to each other and so a slower focal attention mechanism must be used [5].

Other studies, however, have shown that decreasing screen density by spreading out display objects does not always lead to better performance, especially when presenting large amounts of information. Staggers [13] found that in a hospital information system, user performance was best when all relevant information could be seen on one screen. In a simulated power plant control system, Burns [2] found that problems were detected more quickly and accurately using a one-screen, dense display. The advantage gained in both of these studies, however, may not apply to general visual searches because the advantage was preventing the need to look at multiple pages of information.

The effects of the physical structure of a computer screen layout on visual searches were examined by Hornof [10]. Hornof looked at two different of layout structures: labeled visual hierarchies and unlabeled visual hierarchies. Labeled visual hierarchies produced much faster search times than did the unlabeled ones because the labels directed attention to the group most likely to contain the target. Hornof also found that people use slower and more accurate strategies to select a target when distractors are present. Additionally, people are more careful when selecting the target if there are other objects near the target, indicating that spacing between items may play a role in visual search and selection tasks.

Many studies have examined the effects of separating visually presented objects into groups. Tullis [17] even gives guidelines for how information should be arranged into groups. As previously mentioned, Hornof [10] looked at the effects of visual hierarchies and concluded that appropriate labels for groups do improve search times. Treisman [15] studied grouping effects on attention in visual searches for features and objects. In this study, because items could be grouped by features preattentively, attention was given to entire groups instead of individual objects. This should happen when the visual search is for some combination of features, making the search serial. Treisman found that grouping did indeed occur preattentively because groups and not objects were scanned serially. In searches for a single feature, grouping effects did not appear, suggesting that features were detected preattentively. This study showed the important effects that grouping can have on visual searches.

So, while a variety of spatial effects have been studied, the mixed results of those experiments and the indirect mapping of those results to mixed icon/text displays points to the need for further study. Experiment 1 was designed to explicitly assess the F&B model's ability to predict effects of spacing, that is, the distance between the icons on the display.

EXPERIMENT 1

Method

Participants

Participants were 46 undergraduates at Rice University who received course credit for their participation. These participants had at least some prior computer experience and many were experienced users.

Design

The experiment was a within-subjects design and had three independent variables. These were set size, icon quality, and spacing. Set size had four levels with 6, 12, 18, or 24 icons displayed in the search task window.

Figure 1. Examples of icons in three qualities: good, fair, and poor.

Icon quality had three levels: good, fair, and poor. "Good" quality icons were solid circles or triangles shown in red, blue, green, yellow, brown, and black. "Poor" icons consisted of many shapes and lines combined to form complex images and were hard to distinguish from each other. These icons were presented in grayscale. "Fair" icons were relatively simple images that represented some identifiable object. These icons were also shown in grayscale. Figure 1 gives examples of icons used in the study. These icons were the same as those used in the F&B work, and in terms of the ACT-R model differed in the amount of overlap between primitive features. For example, "green triangle" is perfectly predictive in the "good" icon condition because no other icons contained green triangles. However, "gray rectangle" is a very common feature within the "poor" set, so using that feature to guide visual search will often yield icons that do not match the target being sought. Icon labels were randomly selected from a list of 750 words of comparable length.

Spacing had three levels: small, medium, and large. In the small condition, icons were 32 pixels apart. Participants were approximately 15 inches from the screen. At this distance, the 32 pixels between icons in the small condition translated into a visual angle (VA) of 1.6°. Figure 2 shows an example of icons displayed in this arrangement. In the medium condition the icons were 64 pixels apart (VA = 3.2°) and in the large condition the icons were 96 pixels apart (VA = 4.8°). Figure 3 gives an example of icons displayed with large spacing.

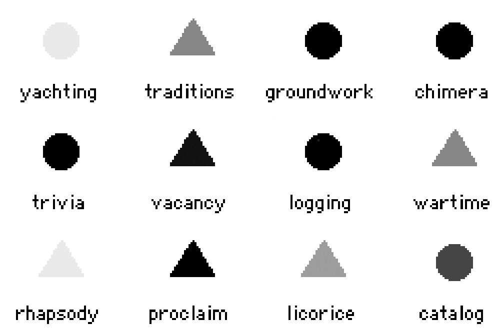

Figure 2. Example of icons displayed in the small spacing condition.

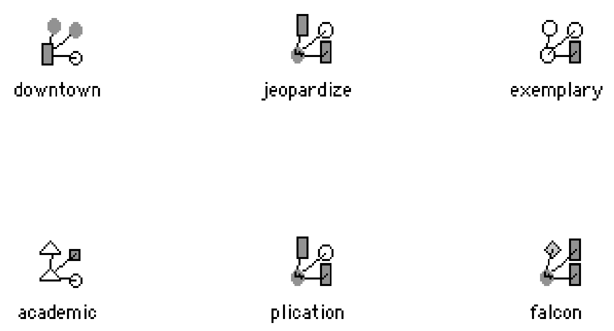

Figure 3. Example of icons displayed in the large spacing condition.

Each independent variable was examined at every level of the other independent variables, yielding 36 trials per block (3 x 4 x 3 = 36). The order of presentation within a block was randomized.

In this experiment, response time was the primary dependent variable, measured from when the participant clicked the "Ready" button to the time when the participant clicked on an icon in the display.

Materials

The computers used to run the experiment were Apple Macintosh iMac personal computers. Display resolutions were set at 600x800. Icons were standard size icons (32 pixels x 32 pixels).

The "Ready" button was set to appear in a location calculated to be the average center of all the icon display windows.

Procedure

Participants were presented with instructions and then a practice block to allow them to become comfortable with the task. After the practice block, participants completed four experimental blocks of trials.

In each trial, participants were presented with one icon and a randomly selected word as the file name (the target). Shortly thereafter, a "Ready" button appeared in the upper left section of the screen. Once they felt they had sufficiently examined the target icon, participants clicked the "Ready" button to proceed to the next phase of the trial. Participants were then presented with a window containing 6, 12, 18, or 24 icons in a grid pattern. The target icon with target label appeared among the distractors in every trial.

The search was a self-terminating mixed search involving both visual and semantic searches, as targets were identified by icon and also by file name. One-third of the icons

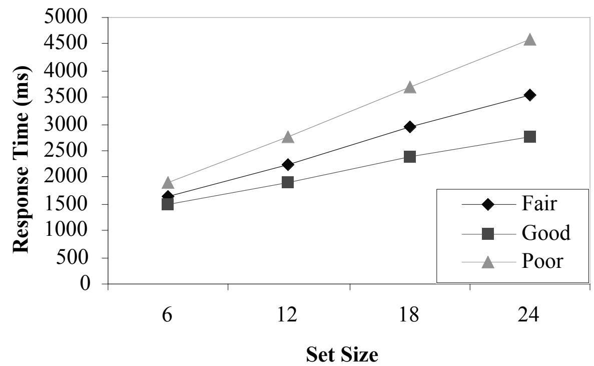

Figure 4. Mean Response Times by Set Size and Quality

displayed in the search task window matched the target icon, but only a single icon had a matching file name label. Matching icons were used to more closely imitate real-world situations in which there are often multiple instances of an icon on a display, such as document icons in a folder. For this same reason, the icons were arranged in a grid formation, such as occurs with the "lock-to-grid" feature many operating systems support. The location of the target within the window was randomized, and the participant searched for and clicked on the target icon. This ended the trial and a new one began.

Results

Mean response times for participants are presented as a function of quality and set size in Figure 4. From this figure, it is apparent that as the set size increased and quality decreased, search time lengthened. Replicating F&B's results, the main effects of set size and quality were both statistically reliable, $F(3, 135) = 607.90$, $p < .001$ and $F(2. 90) = 278.33$, $p < .001$, respectively, as was the interaction between set size and quality, $F(6, 270) = 34.90$, $p < .001$.

However, the goal was not to simply replicate those effects, but to assess the effects of spacing. In Figure 5, response times are displayed as a function of spacing. As the space between icons increased from small to medium to large, search times increased. This was confirmed by a reliable main effect of spacing, $F(2, 90) = 7.267$, $p <.001$. Contrary to what we expected, there was no interaction of set size and spacing, $F(6, 270) = 0.61$, $p = 0.73$, or of quality and spacing, $F(4, 180) = 1.88$, $p = 0.12$.

While statistically reliable, this spacing effect was small in absolute terms; the difference between large and small spacing was only about 150 ms. However, spacing may have affected user behavior in a more dramatic way. The small spacing condition used here was essentially a replication of the conditions in the F&B experiments. Therefore, response times should have been comparable across the two experiments. However, comparisons of the data from these two studies show that the participants in the current experiment were much slower on average than were

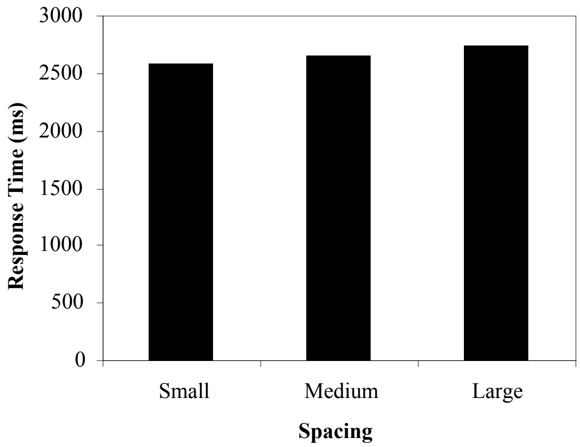

Figure 5. Mean Response Times by Spacing for Experiment 1

participants in the F&B study. Figure 6 shows the mean response times by set size and quality for the two experiments. Because the users in the two experiments came from the same population and the two experimental conditions are the same, one possible explanation for the difference is that the participants in Experiment 1 adopted a new, less efficient search strategy.

This type of strategy change as a result of small differences in the task has been observed before in HCI contexts. The kind of "strategy" referred to here is not necessarily a conscious decision on the part of users, but refers to the way low-level perceptual-motor activities are coordinated by users to accomplish their task. Gray and Boehm-Davis [9] refer to these as "microstrategies." Our data suggested that our users were changing microstrategies.

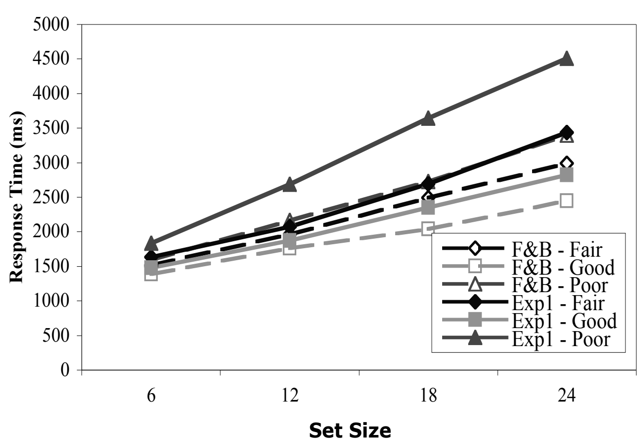

Figure 6. Mean Response Times by Set Size and Quality for F&B and the Smallest Spacing Condition in Experiment 1

MODELING THE EXPERIMENT

Model 1

Our initial model for the experiment was the F&B model, modified very slightly only to make it compatible with the current 5.0 version of ACT-R. This model uses a very efficient search strategy, where shifts of visual attention move from one text label to the next, guided by the nearest icon with a feature matching the target. This model has thus been named the "text-look" model.

No numeric parameters or productions were modified for this model, so this represents a true zero-parameter prediction. Because certain aspects of the model are stochastic, the model was run for 100 blocks of trials.

Comparison of Model 1 Predictions to Data from Experiment 1

In Figure 7, the response times of participants and those predicted by the model are displayed by set size and quality, while Figure 8 displays the model and data by spacing.

The effects of set size and quality predicted by the model match the experimental data in direction, as do the predictions for the effects of spacing. However, for all set sizes, qualities, and spacings, the model predicted that participants would complete the task more quickly than they did, especially for the larger set size and lower quality icons.

Although this model predicted response times that matched the qualitative trends of the experimental data, it did not

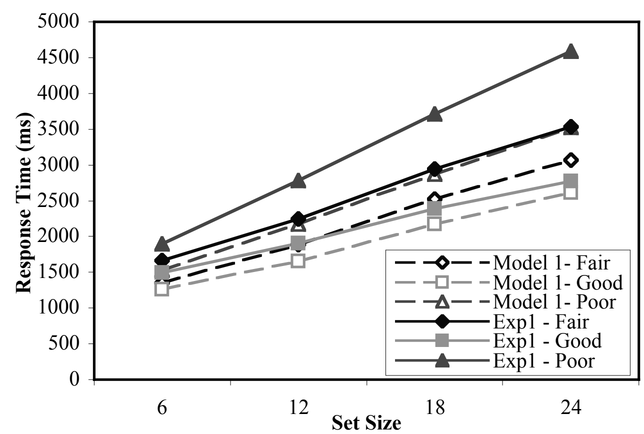

Figure 7. Mean Response Times by Set Size and Quality for Model 1 and Experiment 1

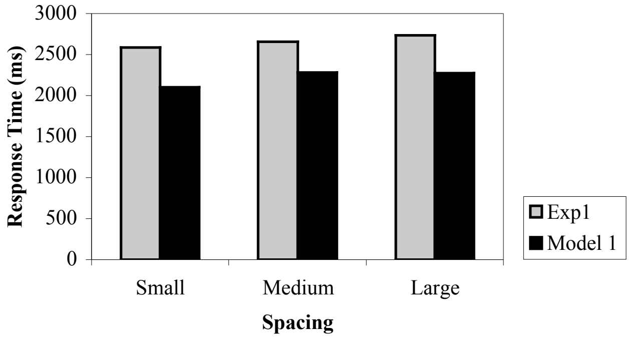

Figure 8. Mean Response Times by Spacing for Experiment 1 and Model 1

provide a particularly good fit quantitatively. Comparing the set size by quality interaction in Experiment 1 and Model 1 produced $R^2 = 0.96$ with a 16.03% mean absolute error, while for the spacing effect, $R^2 = 0.99$ and 16.86% mean absolute error. While this is not bad for a zero-parameter fit, the systematic under-prediction of the model suggested to us that users may have adopted a less efficient search strategy. Model 2 was given a different search strategy and was run to explore this possibility.

Model 2

In this model, the "double-shift" model [8], two shifts of attention are required to examine each icon in the display. The first one shifts attention to any icon that has features matching those of the target icon. The second attention shift is to the file name located beneath that icon. If this file name matches the target file name, attention shifts back to the icon so it can be clicked on. If the file name does not match that of the target, the search process begins again to find another icon with the same features as the target. In addition, this version of the model did not enforce the constraint that the next icon

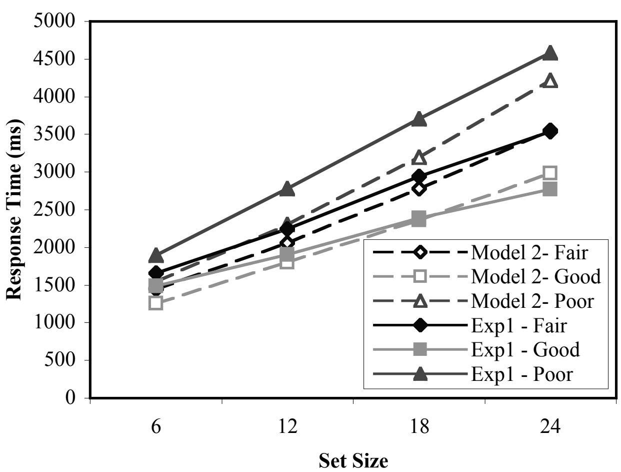

Figure 9. Mean Response Times by Set Size and Quality for Experiment 1 and Model 2

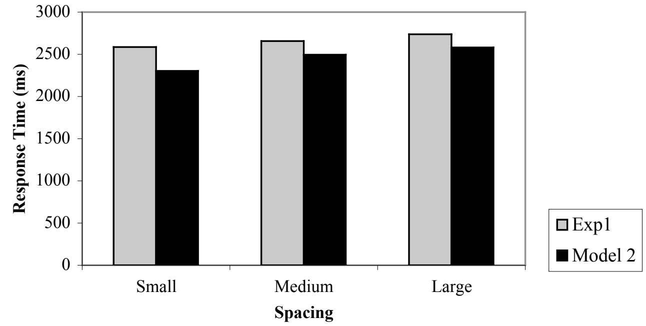

Figure 10. Mean Response Times by Spacing for Experiment 1 and Model 2

examined be the icon nearest the current fixation, as was done for Model 1. This was the only change made to the model; all other parameters were kept constant.

Comparison of Model 2 Predictions to Data from Experiment 1

Model 2 produced a much better fit with the experimental data than did the Model 1. This was true both for quality and spacing effects. The response times of participants and those predicted by Model 2 are displayed by set size and quality in Figure 9.

The response time differences due to spacing from the experimental data and Model 2 are shown in Figure 10. Here, Model 2 also produced a much better fit with the experimental data than did Model 1.

Comparing the set size by quality interaction in Experiment 1 and Model 2 produced $R^2 = 0.95$ with a 9.53% mean absolute deviation. For the set size main effect, the comparison of Experiment 1 and Model 2 yielded $R^2 = 0.97$ and 9.98% mean absolute deviation. Obviously, this model fit the experimental data better than the original model. It still somewhat under-predicts times for the "poor" icons, but is much closer for the other two conditions.

Based on the differences between the F&B results and Experiment 1, and guided by the model, we believe that this spacing manipulation caused an actual change in visual search strategy. When the spacing between icons varied between trials, participants used a much less efficient search strategy. Experiment 2 was performed as an explicit between-subjects assessment of this apparent strategy change.

EXPERIMENT 2

Method

The design, materials, and procedure for Experiment 2 were almost identical to those in Experiment 1. The difference here was that participants were randomly assigned to one of two groups. The VS ("variable spacing") group had 20 participants for whom the experiment was identical to that of Experiment 1 (the spacing between icons still varied between small, medium, and large conditions). The other group, FS ("fixed spacing"), had 12 participants for whom the experiment was the same as that in Experiment 1, except that the small spacing between icons was always used (no spacing changes).

Results

While data was collected from the VS group on larger spacing, we only report results from the smallest spacing used, where the displays participants saw were functionally identical to those in the FS group. That is, there is no difference in the stimuli between the VS and FS groups for the reported comparisons.

The usual effects of set size, $F(3, 90) = 172.41$, $p < .001$, quality, $F(2, 60) = 123.91$, $p < .001$, and their interaction, $F(6, 180) = 12.40$, $p < .001$ were replicated.

Of more interest is how these results compared to the F&B results and to Experiment 1. Figure 11 shows the mean response times by set size and quality for F&B and the FS group of Experiment 2. Overall, this was a fairly good replication of the original results.

Most critical to the current discussion are the results of the VS vs. FS group manipulation. Since the displays seen were effectively identical, but the VS group also saw displays with wider spacing, any differences between the groups must be a result of differences induced by the VS users' exposure to wider spacing conditions. Figure 12 shows mean response times for each group by set size and quality. Between-group differences for the "good" icons are not large, but they are greater for the "fair" icons and quite substantial for the "poor" icons. This was reflected in a reliable quality by group interaction, $F(2, 60) = 5.86$, $p = 0.005$, as well as a reliable

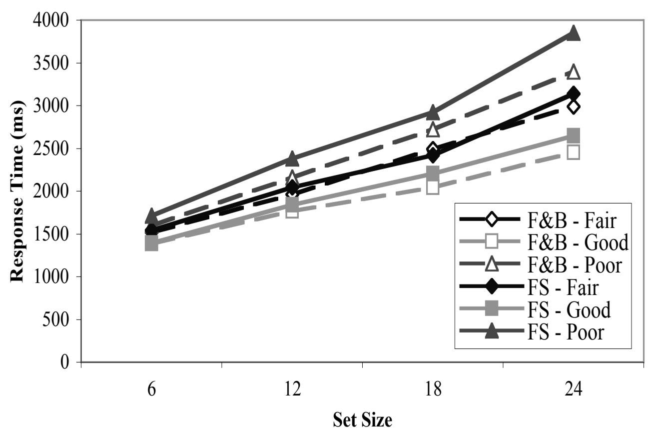

Figure 11. Mean Response Times by Set Size and Quality for F&B and for the FS group of Experiment 2

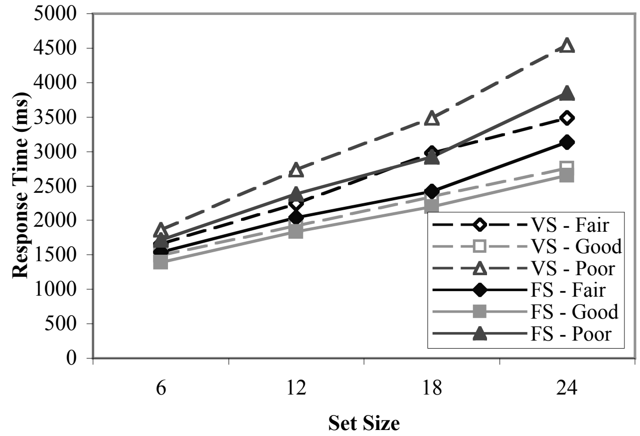

Figure 12. Mean Response Times by Set Size, Quality, and Group for Experiment 2

search slope by group by quality interaction, $F(2, 60) = 4.70$, $p = 0.013$. Thus, we can conclude that the larger spacing conditions seen by the VS group caused them to slow down, even on the more closely-packed displays. We think it unlikely that exposure to wider spacing changed their basic cognitive or perceptual abilities, and so suggest that these users adopted an inferior search strategy, particularly for the "poor" icons.

GENERAL DISCUSSION

First, these results replicate the Fleetwood and Byrne work [6, 7, 8] by showing icons with varying degrees of feature overlap produce different search slopes. However, this was neither the primary intent nor the most interesting finding.

What we found is that varying the spacing between icons does indeed increase search times, as predicted by the ACT-R model. However, it does not do so in the way that we expected. Users in Experiment 1 were substantially slower than we expected or than was predicted by the original ACT-R model. This suggested to us that when the amount of spacing changed, participants employed a different search strategy to find the target icon. This strategy change had a fairly dramatic time cost associated with it, and indeed giving the ACT-R model a less efficient search strategy produced a closer fit to the experimental data. The findings from Experiment 2 replicated this increase in search time as a function of spacing, strongly suggesting a search strategy change when the spacing between icons changed. By using the two models we were able to produce a close fit with the data from both spacing conditions. However, it would be better to have one model that switches the search strategy itself. Future work will attempt to address this issue.

It is unclear whether it was the presence of trials with large spacing intermixed with trials of small spacing or simply the variability of the spacing between trials that caused this effect. Further work will need to be done to distinguish between these two possibilities. Furthermore, it is not clear exactly *why* wider spacing or a change in spacing would produce a strategy change. While the ACT-R model with the less efficient strategy approximately captures the magnitude of the effect, it does not provide insight into why users would make this change in strategy, as the model is perfectly capable of executing the more efficient strategy in the wider spacing situations. Both of these are potential areas of future research, as is eye-tracking to more concretely confirm this strategy switch and to gain a better sense of exactly what strategies users are employing. Based on our own intuitions and the ACT-R model, we had no *a priori* reason to expect such a difference.

The strategy change found in these experiments highlights the importance of understanding how the visual layout of a computer screen affects the eye movements that control the visual search process. Subtle manipulations can have surprisingly large impacts on overall performance; in Experiment 2 at the largest set size, users in the VS condition were almost 20% slower than users in the FS condition. We submit that most display designers (ourselves included) would not have foreseen the magnitude of this effect. When one considers high-risk environments such as automobiles or even how many times per day most users search for icons on computer screens, it is easy to see how this could have a substantial impact on safety and productivity.

REFERENCES

1. Anderson, J. R., Bothell, D., Byrne M. D., Douglass, S., Lebiere, C., & Quin, Y. (in press). An Integrated Theory of the Mind. *Psychological Review*.
2. Burns, C. M. (2000). Navigation strategies with ecological displays. *International Journal of Human-Computer Studies, 52*, 111-129.
3. Byrne, M. D. (1993). Using icons to find documents: simplicity is critical. *Proc. ACM INTERCHI'93 Conference on Human Factors in Computing Systems*, 446-453.
4. Byrne, M. D. (2003). Cognitive Architecture. J. Jacko & A. Sears (Eds.), *The Human-Computer Interaction Handbook: Fundamentals, Evolving Technologies, and Emerging Applications* (pp. 97–117). Hillsdale, NJ: Erlbaum.
5. Cohen, A. & Ivry, R. B. (1991). Density Effects in Conjunction Search: Evidence for a Coarse Location Mechanism of Feature Integration. *Journal of Experimental Psychology: Human Perception and Performance, 17*(4), 891-901.
6. Fleetwood, M. D. (2001) Computational Modeling of Icon Search. Master's Thesis. Rice University: Houston, Texas.
7. Fleetwood M. D. & Byrne, M. D. (2002). Modeling Icon Search in ACT-R/PM. *Cognitive Systems Research, 3,* 25-33.
8. Fleetwood, M. D. & Byrne, M. D. (2003). Modeling the visual search of displays: A revised ACT-R/PM model of icon search based on eye-tracking and experimental data. *Proceedings of the Fifth International Conference on Cognitive Modeling,* 87-92.
9. Gray, W. D. & Boehm-Davis, D. A. (2000). Milliseconds Matter: An Introduction to Microstrategies and to Their Use in Describing and Predicting Interactive Behavior. *Journal of Experimental Psychology: Applied, 6*(4), 322-335.
10. Hornof, A. J. (2001). Visual search and mouse pointing in labeled versus unlabeled two-dimensional visual hierarchies. *ACM Transactions on Computer-Human Interaction, 8*, 171-197.
11. Salvucci, D. D. (2001). EMMA: An Integrated Model of Eye Movements and Visual Attention. *Cognitive Systems Research, 1*, 201-220.
12. Smallman, H. S. & Boynton, R. M. (1990). Segregation of basic colors in an information display. *Journal of the Optical Society of America. A, Optics, image science, and vision, 7*(10), 1985-1994.
13. Staggers, N. (1993). Impact of screen density on clinical nurses' computer task performance and subjective screen satisfaction. *International Journal of Man-Machine Studies, 39*, 775-792.
14. Thacker, P. P. (1986). Tabular displays: A human factors study. Doctorial Dissertation. University of South Florida: Tampa, Florida.
15. Treisman, A. (1982). Perceptual Grouping and Attention in Visual Search for Features and for Objects. *Journal of Experimental Psychology: Human Perception and Performance, 8*(2), 194-214.
16. Treisman, A. M. & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12,* 107-141.
17. Tullis, T. S. (1997). Screen Design. *Handbook of Human-Computer Interaction*. 2nd ed. Helander, M., Landauer, T. K., & Trabhu, P. (eds.). Elviser: New York.
18. Wolfe, J. M. (1994). Guided Search 2.0: A revised model of visual search. *Psychonomic Bulletin & Review, 1* (2), 202-238.