Cognitive Engineering Laboratory

An Experimental Evaluation of Transparent Menu Usage

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- Understanding control strategy differences between people of various levels of expertise within the context of process control systems.
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- Evaluating existing human factors handbooks.
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ABSTRACT

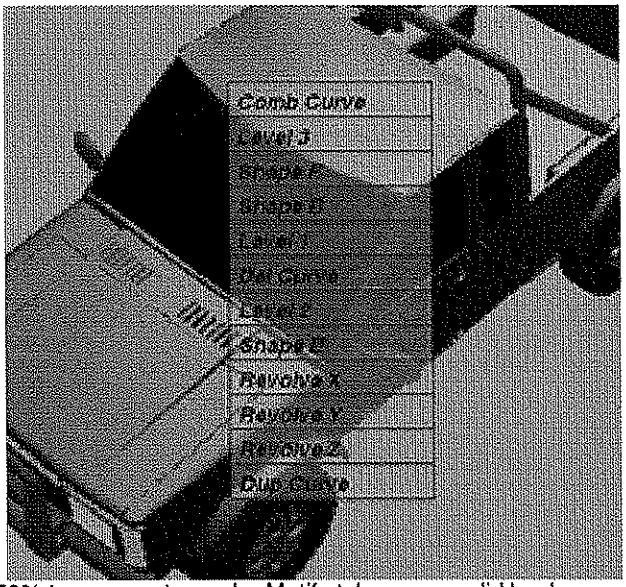
This paper reports on our on-going efforts to systematically evaluate transparent user interfaces It reflects our progression from theoretical experiments in focused attention to more realistic application based experiments on selection response times and error rates. We outline how our previous research relates to both the design and the results reported here. For this study, we used a variably-transparent, text menu superimposed over different background content: text pages, wire-frame images, and solid images. We also evaluated both "standard" text (i.e., Motif style, bold Helvetica, 14 point) and a proposed font enhancement technique ("Anti-Interference" outlining) This experimental evaluation provides both valuable insights into potential design parameters and suggests a systematic evaluation methodology.

KEYWORDS: display design, evaluation, transparency, user interface design, interaction technology, toolglass

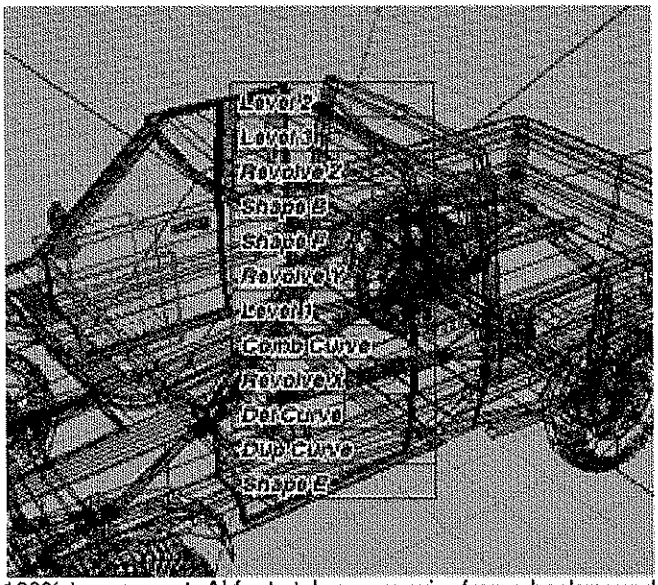
INTRODUCTION

This paper reports on an experimental evaluation using variably-transparent, linear menus superimposed over different background content: text, wire-frame images, and solid images (Figure 1). The menu contains text items presented in either regular Motif-style fonts or our proposed "Anti-Interference" (AI) font. We evaluated the effect of varying transparency levels (from opaque menus to highly-transparent menus), the visual interference produced by different types of background content, and the performance of AI fonts.

In our previous research, we evaluated a *theoretically motivated experiment* (The Stroop Experiment [4]), which tested a hypothesized model of focused attention and interference. The results of this experiment allowed us to modify our model and provided threshold transparency values for verbal response times under stringent, controlled conditions. The stimuli for this experiment were specific to the Stroop Effect [7] and therefore were necessarily



50% transparent, regular Motif style menu, solid background



100% transparent, AI font style menu, wire frame background

FIGURE 1. Experimental Sample Images

simplistic and non-representative of real applications. (The stimuli were a variably transparent color patch superimposed over a text word.) We subsequently ran a more "applied" experiment using variably *transparent icon palettes* superimposed over different background images [5]. In this case, the stimuli were substantially more complex and realistic than those used in the Stroop Experiment, at the expense of some experimental control. The Icon Palette Experiment confirmed the viability of our methodology and provided a means for linking the theoretical Stroop results to a more realistic application–based experiment. However, icon palettes represent only one small subset of user interface tools.

The study described in this paper represents an "applied" experiment to evaluate *transparent menu selection* tasks, but can be applied to text legibility overall. One of the most general user interface mechanisms involves item selection from either a window or from a linear menu, where text labels are predominant. These text labels are either selectable in themselves (e.g., as menu items) or they are important cues in differentiating and identifying graphical window items for subsequent selection (e.g., radio buttons or sliders). In addition to windows and menus, we wish to apply transparency to help systems and on-line documentation. Clearly the effect of transparency on text legibility is therefore a significant factor in the usability of such interfaces and tools.

Using the approach developed in our previous experimental work, we have created a new set of stimuli to test performance for text legibility under varying transparency conditions. We also systematically evaluate a proposed optimization, "Anti–Interference" fonts, to determine if such enhancement techniques significantly improve the usability of transparent interfaces.

OTHER WORK IN TRANSPARENCY

In recent years, a number of researchers have proposed interesting and novel designs which incorporate the notion of transparent objects. (For a brief synopsis of these systems please refer to [4] and [5].) One notable point is the lack of evaluative data reported thus far, which quantifies performance or usability of these systems as it relates to transparency. One purpose of our paper therefore, is to provide evaluation methodologies and empirical results which could be directly applied to these other systems.

We wish to emphasize that the intriguing "transparency" applications not only demonstrate the variety and novelty of transparent user interface design, but are also clearly striving towards more integration between task space and tool space, between multiple tools, or between multiple views. Focused attention and visual interference play a significant role in the success or failure of such integration and of the designs themselves.

COMBINING EXPERIMENTAL CONTROL WITH REALISM

Our research approach combines theoretical experiments, "applied" experiments, and field studies. Each element of this approach reflects a progressive increase in realism, at the expense of some experimental control. However, the same systematic methodology can be consistently applied in each case.

The Menu Selection Experiment described here, combines experimentally controlled conditions with realistic stimuli. The menu items are similar to some used in a commercial product, though generally they are not used together on the same menu in the real application. We deliberately chose visually similar text labels to test legibility, for example, "Revolve X", "Revolve Y", and "Revolve Z". We constructed the target menu to match the Motif style window menus presented on the SGI, in terms of font type, style and size (Helvetica, bold, italic, 14 point was used). The background content images were also selected from a set of real working images contained in the product library as released to customers. The experiment evaluated whether subjects could identify randomly selected items within the target menu, given the backgrounds. The use of menus over library images does reflect realistic usage of UI tools for this product.

EXPERIMENT - TRANSPARENCY & MENU LEGIBILITY

This experiment explores the issue of focused attention and interference in the context of text legibility and menu selection. The menu appeared in the foreground and various images appeared in the background (e.g., Figure 1, 2). The menu transparency level varied randomly. Sometimes it was opaque (0% transparent), blocking out

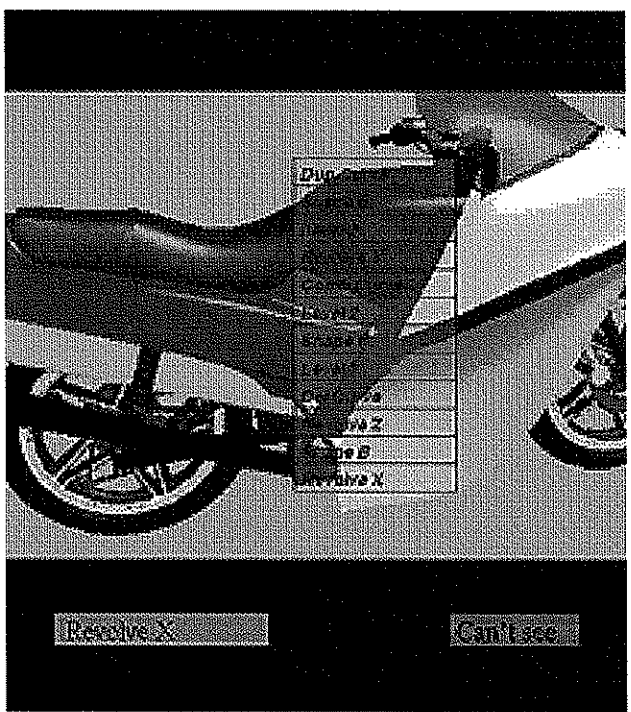


FIGURE 2. Sample Trial Screen showing target item, stimulus image and "can't see" option

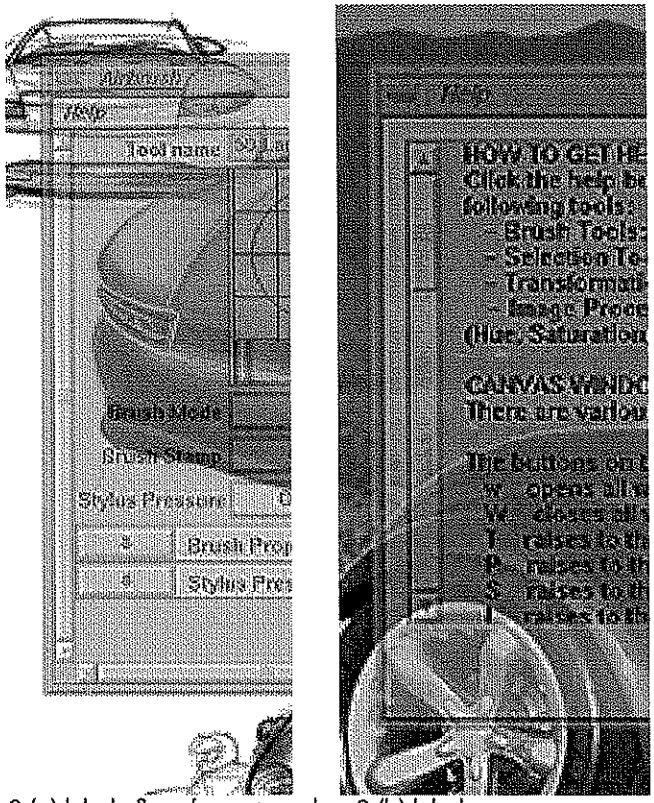
the background (traditional menu appearance). Other times the background could be easily seen *through* the menu (e.g., 100% transparent or clear). We used a "regular" Motif style font (Helvetica, bold, 14 point, italic) and our proposed Anti-Interference (AI) font, which uses luminance values to create a contrasting outline (Figure 5). All combinations of font styles X background types X transparency levels were run.

For each trial, subjects were shown a target menu item to study (lower left corner, Figure 2). When ready, subjects pressed a "next trial" button (not shown) which displayed the menu superimposed over the background at a randomly ordered transparency level. Items were randomly distributed on the menu. Subjects had to locate and click on the target item within the menu. If they could not see the item on the menu (i.e., illegible) they could press a "can't see" button. Response times and errors were logged. The target item remained on the screen throughout the trial for reference purposes.

A Predictive Model based on Previous Experiments

The Menu Selection Experiment represents a *foreground* focused attention task and, as such, we anticipate a performance curve which resembles those found in the Icon Palette Experiment (i.e., opaque levels should have "good/fast performance" and transparency increases should degrade performance) (Graph 1 and 2). This basically implies that the menu items will be sensitive to visual interference from the background as transparency increases. However, unlike the palette selection task where the *entire* icon was made transparent, the menu label remains opaque – only the surface area *around* the label is made transparent (e.g., Figure 1b, 3b, 5b). We believe that this difference reflects a realistic and reasonable design choice. In the palette selection experiment, our icons were solid objects (as many icons typically are). In order to achieve a transparency effect, the icon image itself must be made transparent. In the case of text labels however, the text occupies only a small percentage of the "selectable region", therefore we may leave the text opaque and still achieve reasonable transparency using the remainder of the selectable area around it (e.g., Figure 3b). (Both design alternatives are shown in Figure 3. We feel Figure 3b represents the more realistic design choice. This was the method used in our experiment.)

The menu selection task itself is a legibility or word naming task suggesting cut-off points similar to those from the Stroop Word Naming Experiment [4] (Graph 3). Best performance is expected to be maintained from 0% (opaque) to 50%; no further improvements occur beyond increases of 50% transparent (i.e., interference is no longer an issue). Poor performance is reached at about 90% (i.e., 10% of the foreground shows, 90% of the background shows)and does not deteriorate further . In this latter case, (as in the Stroop Experiment), interference strongly effects both response time and error rate such that the transparency levels between 90% and 100% are virtually unusable. However, these cut-off points are based on experiments where the *entire* target object was transparent. We believe

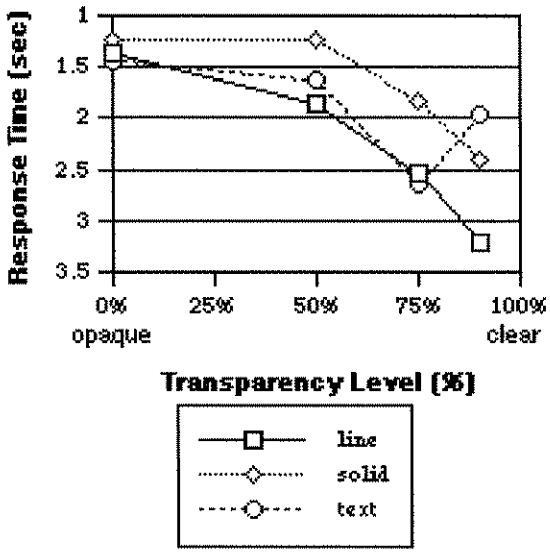


3 (a) labels & surface around labels are both transparent

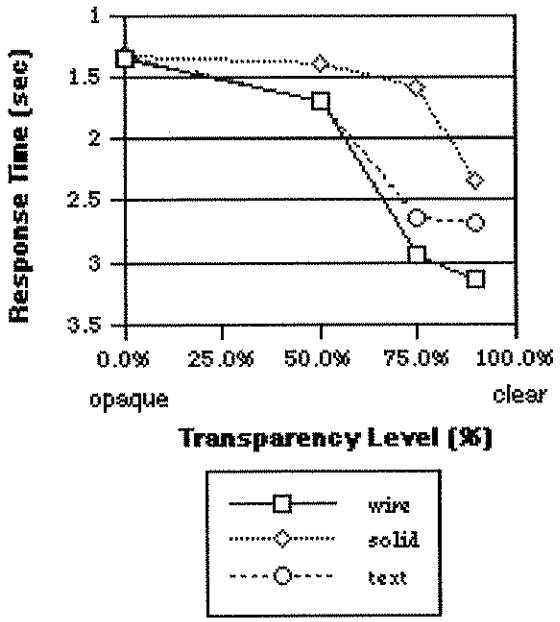
3 (b) labels are opaque, surface around labels is transparent

FIGURE 3. Comparison of design alternatives for transparent text items.

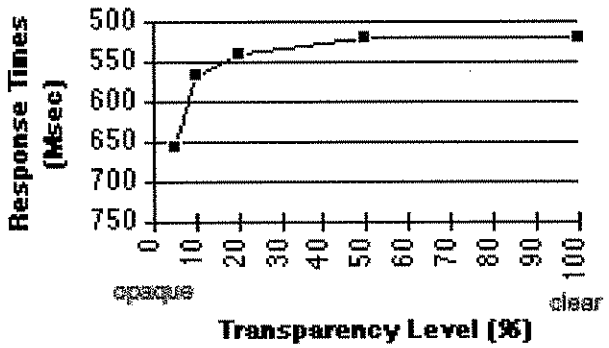
that the cut off points might shift right on the hypothesized curve, given the opaque text labels – implying more resistance to visual interference. Based on extrapolating these previous experimental results, our predicted curves and cut-off points are shown in Figure 4.



GRAPH 1. Icon Palette Experiment Mean Response Times for Icon Type



GRAPH 2. Icon Palette Experiment
Mean Response Times for Background Types



Graph 3. Mean Response Time Results from the Stroop Experiment - **Word Naming** Task

When applying the Anti-Interference (AI) fonts, we anticipate more interference–resistant images, therefore the low-end and high-end performance cut-off points would be higher (as depicted in Figure 4, "AI font" curve). (This is not unlike the effect shown in Graph 1 and 2 when the complexity of the image was simplified, for example, from text to solid).

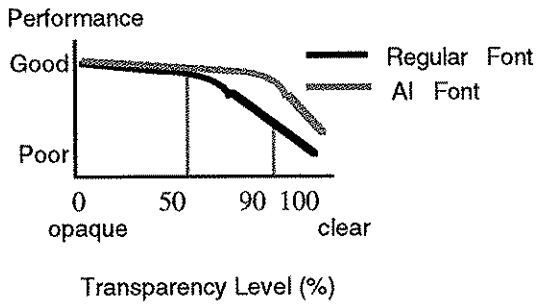
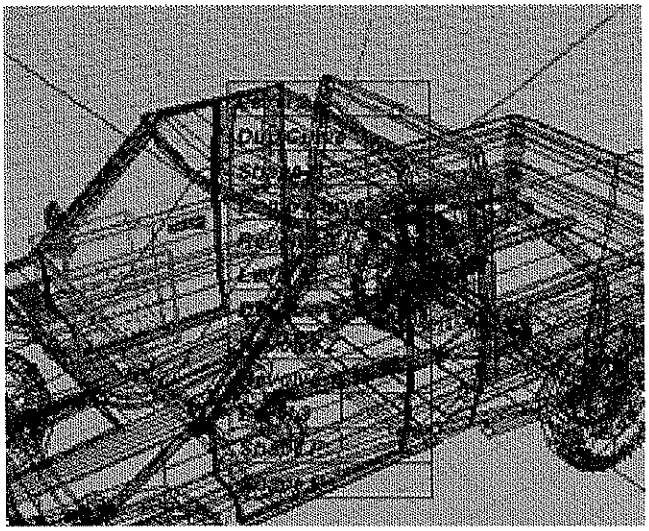
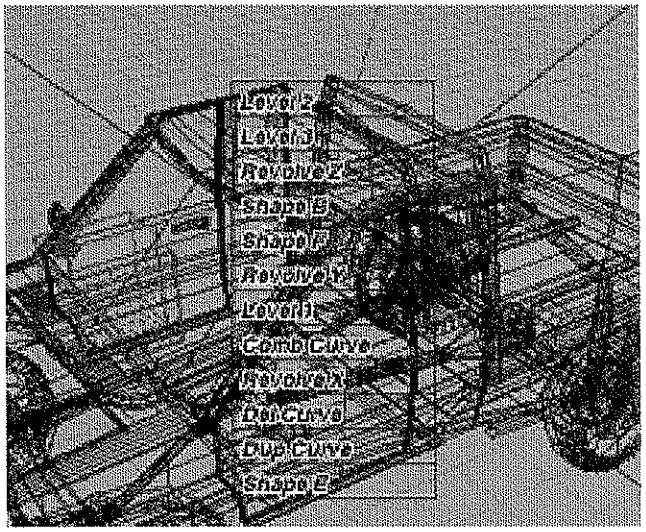


FIGURE 4. Projected curves - Menu Selection Experiment



5 (a) Regular fonts, 100% transparent, wire bkgrnd



5 (b) AI fonts,100% transparent, wire bkgrnd

Hypotheses (stated as <u>null</u> hypotheses)

H1: As transparency level increases (i.e., the background is more visible through the menu) the response time and errors will be unchanged.

We anticipate *more* interference as transparency increases and therefore reduced performance (slower response time and increased errors).

H2: The content of the background image (text, wire frame, solid) will have no interaction effect with legibility of the items.

We anticipate that increased complexity or information density on the background will make menu legibility decrease. Text backgrounds will have the worst performance, followed by wire-frame, then solid images.

H3: AI fonts will have no effect on performance (i.e., no difference over regular fonts).

We anticipate that AI fonts will significantly improve performance by creating more interference resistant text.

Lastly, we wish to verify whether our proposed cut off points at 50% and 90% are reflected in the data.

Experimental Design

A fully randomized, within subject, repeated measures design was used. There were three independent variables: type of font, type of background, and transparency level. A total of 540 trials were run for each subject. Trials were presented in random order. Each session lasted about 45 minutes. Dependent variables of selection response time (based on a mouse click) and errors were logged. Two error conditions were possible: the subject pressed the "can't see" button indicating that the item was not legible, or the subject selected the incorrect menu item. In the latter case, the item selected and it's location were logged. Error trials were removed from subsequent analysis of response time data. Error data was analyzed separately.

We used 2 groups of menu items: each group was visually similar to ensure true legibility performance. The menu items were: Revolve X, Revolve Y, Revolve Z, and Dup Curve, Comb Curve, Del Curve. Six other menu items were randomly distributed with the target items. (A 12 item menu was felt to be representative of the average menu/menu size used within the actual product.) Items were randomly assigned positions within the menu for each trial. This was done to ensure the experiment was not confounded by subjects learning the position of items. The target item was presented to the subject throughout the trial as a reminder. This was to prevent memory errors (which we were not testing for).

We randomly assigned background images of three types: text pages, wire frame images, and solid images. Three samples of each type were created. Images were 8-bit color rendered images. These backgrounds were aligned such that a major portion of the content was directly under the menu.

We randomly assigned the level of transparency to the menu. These levels were based on our previous experimental experience [4, 5] and test pilot results with this experiment. Levels of 0% (opaque traditional menus), 50%, 75%, 90% and 100% (clear) were used. The opaque level represented the baseline condition where the fastest performance was anticipated.

Finally, we randomly assigned either regular font style or our AI font style to the items. Regular fonts were matched to the Motif style menus that appeared from windows on the SGI (Helvetica, 14 point, bold, italic was the best match). We developed Anti–Interference fonts as a potential interference resistant font technique (Figure 5b). Since an AI font has two opposing color components, it remains visible in any color background.

It is well known that contrast is the most critical dimension of visibility. In AI fonts, the opposing outlines of the text are rendered in a color which has the maximal contrast to the color of the text. For any selected text color vector [R, G, B], our AI font algorithm calculates the luminance value Y according to the YIQ color model used in television broadcasting ([3], page 589). Note that the red, green and blue components are not equally weighted in contributing to luminance.

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.275 & -0.321 \\ 0.212 & -0.528 & 0.311 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

Based on the value of Y, our algorithm then determines the outline color with the maximal luminance contrast. In practice, only two color vectors can be the candidates for the solution: [0,0,0] (black) when $Y>Y_{max}/2$ or $[R_{max}, G_{max}, B_{max}]$ when $Y<Y_{max}/2$, where Y_{max} is the maximum luminance value and $R_{max}, G_{max}, B_{max}$ are the maximum red, green and blue value respectively.

Experimental System Configuration

The experiments were run on an SGI Indy™ using a 20 inch color monitor. Subjects sat at a fixed distance of 60cm from the screen (average distance when working normally).

Procedure

Subjects were given 20 practice trials. These trials were randomly selected from the set of 720 possible combinations. Following this, subjects were shown the target item for each trial and a button to start each trial when they were ready. They could take short rest breaks whenever necessary. Response times and errors were logged. Response selections were made using the mouse. Subjects were debriefed at the end of the experiment. Open ended comments were recorded.

Subjects

A total of 10 students from the University of Toronto were run as subjects. They were pre-screened for color-blindness and for familiarity with the product from which the images and items were taken. Subjects were paid for their participation and could voluntarily withdraw without penalty at any time.

RESULTS

We have categorized our results by Response Time analysis, Error analysis, and comments from the interviews with subjects. The analyses for all 10 subjects are presented below. Background types were analyzed by each individual image and by category (i.e., text page, wire frame, solid). Font styles were AI versus regular font. Transparency levels were analyzed according to the 5 levels used: 0% (opaque), 50%, 75%, 90%, 100% (clear).

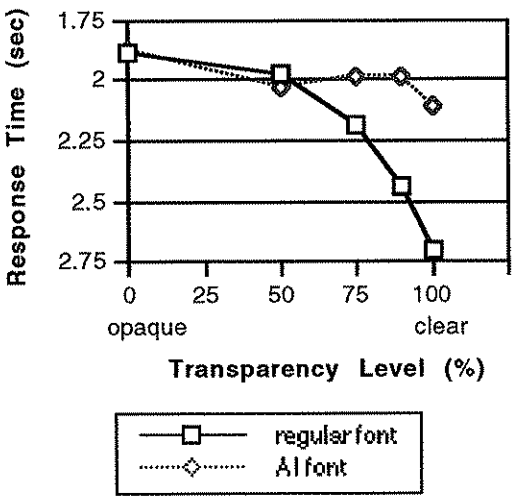
Quantitative Statistical Analysis - Response Time

Highly significant main effects were found for all of our major variables: background type, transparency level, and font type (Table 1). However, we are primarily interested in the transparency and font effects and their interactions with background type. Statistically significant interaction effects were found for background X font, background X transparency, and background X font X transparency (Table 1).

condition item X bkgrnd X transp	df	F value	p<
background type	8, 5051	4.48	.01
transparency level	4, 5051	38.28	.0001
font type	1, 5051	64.75	.0001
bkgrnd type X font type	8, 5051	6.98	.001
bkgrnd type X transp	32, 5051	2.44	.01
bkgrnd X font X transp	32, 5051	3.76	.001

TABLE 1. Statistical Results for Main Effects and Interactions

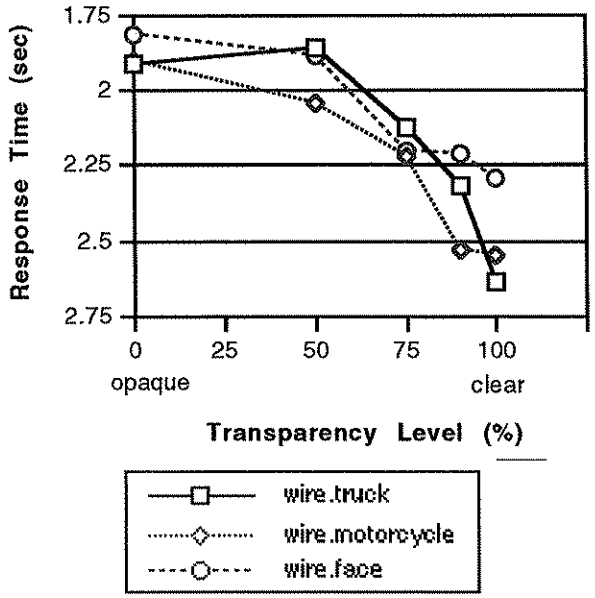
The primary results of interest are plotted below (Graph 4 and 5a, b, c). Graph 4 depicts the interaction between font style and transparency level. Graph 5 a, b, show the interaction between background types and transparency level. (These were collapsed across all subjects and menu target items.)



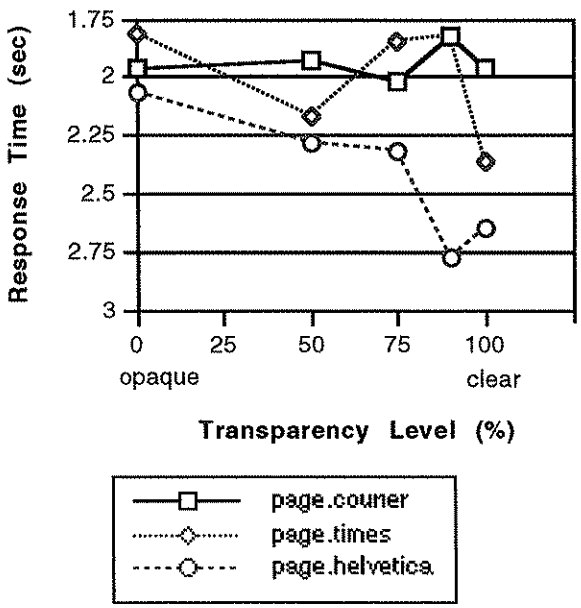
GRAPH 4. Mean Response Times for Transparency Levels X **Font Style** (across all background types)

To determine if the differences are significant between the individual lines plotted within each of the graphs, a Student-Newman-Keuls (SNK) test was run post-hoc as a comparison of means. (This determines the clustering of items within font type, background type, and transparency level. and indicates which items are not statistically different.) The results of the post-hoc analyses are described below.

We subsequently ran a finer grained analysis *at each transparency level.* At the opaque menu level (0%) and the 50% transparent level, there were no statistical differences between background types or between font styles (AI versus regular). At 75%, 90%, and 100% transparency the AI font performed significantly faster than the regular font (as shown in Graph 4). There are also significant differences between background types at these level, though these differences are not based on the category (text, wire, solid) but rather on the individual image properties. For example, the text pages each used a different font style, one of which was Helvetica 14 bold (purposely matching the menu item font style). This page performed

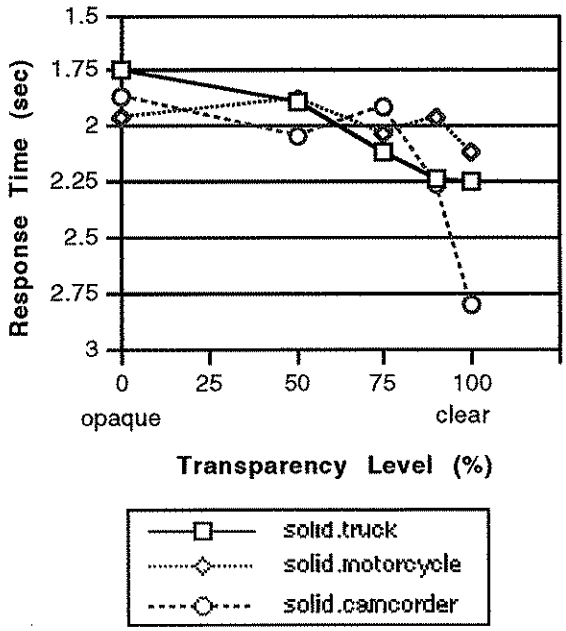


GRAPH 5a. Mean Response Times for Transparency Levels X **Wire** Background Types (across font types).



GRAPH 5b. Mean Response Times for Transparency Levels X **Page** Background Types (across font types).

significantly slower than the other pages. The denser wire frame images (i.e., more complex meshes and therefore also darker in color) performed significantly slower than the simpler wire frame. The solid images with black components (the truck and the camcorder), performed significantly slower than the solid multi-colored motorcycle image. (These images were used to create a worst case scenario of black menu item fonts over partially black background content.) At the 100% (clear) level, images with black components were clearly the most difficult.



GRAPH 5c. Mean Response Times for Transparency Levels X **Solid** Background Types (across font types).

We also ran subsequent analyses on the font style. Regular menu fonts showed strong interaction effects with the matched text page background and the dense wire frame backgrounds. The solid images with black components also performed poorly. Somewhat surprisingly, the best (most interference resistant) backgrounds were the non-matched text pages. There were statistically significant differences between the following transparency levels: 100% - poorest, 90%, 75%, and 50% + 0% (which performed equivalently well. (This finding is supported by our earlier Stroop Experiment results and Icon Palette Experiment results.)

AI fonts were relatively insensitive to the type of background, the matched text page showed the worst performance. Other background images were not significantly different. There were statistically significant differences between the following transparency levels: 100% - poorest, 50%, 75% + 90% (not different), 0%.

Targeting Error Results

Error trials were removed from the analysis of response time data and were subsequently analyzed separately. In total 1% of the trials resulted in *targeting errors* or misses. There were two types of targeting error possible: accidental selection of an adjacent menu item (45% of total) and substitution of an incorrect menu item (55%). The latter case, the user incorrectly identified the target item by replacing it with a similarly named item such as Revolve X instead of Revolve Y.

The adjacency item errors are most strongly influenced by the width of the target areas. This was matched to standard Motif menu widths and so we did not wish to increase the width size, reducing these errors. However, we are most interested in substitution misses. These are partially attributed to poor visibility of the target item in the menu and mis-reading the menu. Several subjects immediately realized when they had made such substitution errors ("oh no, I meant to select Revolve X, not Y"). The breakdown of substitution errors is shown in Table 2 below. These errors were surprisingly evenly distributed across transparency levels.

transparency level	number of trials
0% - opaque	9
50%	5
75%	6
90%	3
100% - clear	8

Table 2. Errors due to target misses by substitution

The substitution errors were also evenly distributed across font type for each level. AI fonts made little difference in reducing these errors.

Legibility "Error" Results

Of the total error trials, 48% were those that subjects marked as "can't see" (which we believe prevented subjects from guessing randomly). In total, less than 1% of the trials run were marked "can't see". The breakdown by transparency level is shown in Table 3. Note that almost all of the legibility errors occurred at the 100% level. All of these illegible trials were in the regular font condition (i.e., no AI font trials were marked illegible).

At the 90% level, menu items appearing over the text page or wire frame backgrounds were illegible. At the 100% level, the two solid backgrounds with black color components accounted for *70%* of the illegible trials. (The menu font was black and therefore one would expect these trials to be illegible). However, surprisingly, text pages accounted for only 3% of the errors made at this level.

transparency level	number of "can't see" trials	% of legibility errors
0% - opaque	0	0%
50%	0	0%
75%	0	0%
90%	6	10%
100% - clear	51	90%

Table 3. Trials marked as illegible

The mean response time for legibility errors was 6.84 seconds (the "give up" time), almost 3 times the response time for other trials. This implies that subjects exerted substantial effort to respond to each trial before giving up. In effect, this figure represents the "tolerance threshold" beyond which it is too much effort to locate the target.

Qualitative Results

Subjects commented that the wire frame backgrounds seem the most difficult in general and the solid backgrounds were

the easiest. However, subjects also noted that highly transparent menus over black backgrounds were very hard. Most subjects commented that even a small change in the transparency level (from 100% clear to 90%), made a substantial difference in these back–on–black conditions. This change allowed subjects to see and select items where previously they marked the trial "can't see".

Subjective preference seemed to favor changing the transparency level to improve visibility, as opposed to changing to the AI font. Several subjects commented that they did not like the "outline font" and if given a choice, preferred the 50% transparency level.

DISCUSSION

As predicted in Figure 4, transparency levels significantly effected response time and error rates (independent of font type or background). Also, we found evidence to support our predictions about the relationship between Regular font performance and AI font performance. The AI fonts produced a substantially flatter performance curve, shifted towards better (i.e., faster) performance. This implies they are more interference resistant. The real advantage of using AI fonts was only realized at higher transparency levels (i.e., over 50%). In fact, AI fonts at 75% and 90% transparency produce results similar to those of using unmodified fonts at 50% transparency. This might be used as a design trade-off for text–based transparent interfaces.

Menu selection X background content interactions were most strongly effect by highly transparent levels. There are not large performance differences between 0% to 50% transparency. (This is consistent with results from our Stroop Experiment and the Icon Palette Experiment.) Surprisingly, the text backgrounds produced much better performance than expected. The most critical dimension of interference with text menu selection tasks was color conflict. The closer in shade and hue the background is to the menu text color, the higher the interference and worse the resulting performance.

CONCLUSIONS

This experiment was optimized for a menu selection (i.e., foreground) focused attention task, while preserving an *awareness* of the background. The results are appropriate for selection of foreground items. However, other tasks have requirements for more than just awareness of the background. For example, the ToolGlass system [1, 2, 6] requires alignment of the palette item with a specific background object or area. In this case, background visibility requirements are higher than that require for awareness. The goals of the task must be taken into account in order to assess the priorities of foreground versus background visibility. To better understand these differences, studies on background selection or alignment tasks are also needed.

This paper presented results for using text superimposed over a variety of background images. We illustrated a method for empirically evaluating transparent user interfaces in this context. This methodology can be generalized to other types of interfaces by incorporating images or backgrounds from *any* target application or working product. The idea is to capture realistic screens at a single moment in time. With these captured images, any sort of menu, window, or palette can be superimposed at varying transparency levels and tested. Using this approach, performance can be predicted and the most appropriate settings can be determined for a variety of target applications. These empirical results can be combined with subjective assessments to provide strong insights about the most and least preferred design solutions in a generalizable way.

In addition to the empirical research described in this paper, we are additionally investigating long term usage of systems which incorporate transparent tools or windows. Our interest is in providing user interfaces which improve the fluency of work by better integrating the tools with the task space.

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