Visual Selective Attention Deficits in Patients With Parkinson’s Disease: A Quantitative Model-Based Approach

W. Todd Maddox
Arizona State University

Dean C. Delis
University of California, San Diego, and Veterans Affairs Medical Center, San Diego

J. Vincent Filoteo
University of Utah

David P. Salmon
University of California, San Diego

Seventeen Parkinson’s disease (PD) patients with no dementia and a group of matched normal controls were administered a visual attention task. A set of quantitative models were developed and applied to the data (W.T. Maddox & F.G. Ashby, 1993). These models provided a description of the nature of individual error distributions. The results suggested that (a) PD patients were not differentially impaired as compared with normal controls in their ability to integrate information from 2 stimulus dimensions; (b) a significantly larger proportion of the PD patients as compared with normal controls showed deficits in selective attention; and (c) although a large subgroup of the PD patients showed selective attention deficits, another subgroup of PD patients was able to attend selectively in an optimal fashion. The possible neuropathological correlates of PD patients’ selective attention deficits are discussed.

Past studies indicate that patients with Parkinson’s disease (PD) are impaired on tasks of visual perception (Boiler et al., 1984; Hovestadt, de Jong, & Meerwaldt, 1987; Levin, 1990; Levin, Liabre, Ansley, Weiner, & Sanchez-Ramos, 1990; Raskin et al., 1990). However, there is growing controversy regarding the underlying mechanisms of PD patients’ deficits on these tasks. Whereas some investigators argue that these data provide evidence for a specific visual-perceptual deficit in PD (Boiler et al., 1984; Hovestadt et al., 1987; Levin, 1990; Levin et al., 1990; Raskin et al., 1990), other researchers have suggested that PD patient deficits on these tasks may be related to impairment in other cognitive processes. For example, some studies have suggested that PD patients’ deficits on tasks of visual perception may be related to deficits in executive functions (Bondi, Kaszniak, Bayles, & Vance, 1993; Grossman et al., 1993), shifting cognitive set (Bowen, Burns, Brady, & Yahr, 1976; Brown & Marsden, 1986) and motor functions (Brown & Marsden, 1986; Girotti et al., 1988; Stelmach, Phillips, & Chau, 1989).

Another cognitive mechanism that may be related to PD patient impaired performance on tasks of visual perception is a deficit in attention. It is now widely believed that visual perception is not a unitary cognitive operation; rather, it encompasses several different component processes (e.g., Marr, 1982; Uttal, 1981). One important aspect of visual perception is the ability to attend selectively to a visual target in the presence of irrelevant visual information (e.g., Garner, 1974; see Maddox, 1992, for a review). Several studies indicate that patients with PD may be impaired on visual attention tasks (Filoteo et al., 1994, 1995; Wright, Burns, Geffen, & Geffen, 1990; Yamada, Izyumi, Schulzer, & Hirayama, 1990), but more specifically, previous work demonstrates that PD patients can be impaired on tasks of visual selective attention. For example, PD patients demonstrate abnormal performance on the Stroop task, which requires subjects to attend selectively to the color of words while ignoring the actual word itself (Henik, Singh, Beckley, & Rafal, 1993; Hietanen & Tervainen, 1986; Stank et al., 1993). These patients are also impaired on visual search tasks that require subjects to attend selectively and localize targets among distractors (Pillon et al., 1989; Villardita, Smirni, & Zappala, 1983) and on tasks that require them to attend selectively to visual displays while having to perform extraneous tasks simultaneously (Sharpe, 1990). Given that visual attention may be necessary to perform visual-perceptual tasks and that PD patients demonstrate deficits in visual attention, it is possible that their poor performances on visual-perceptual tasks are related to a fundamental deficit in attention.

The finding that PD patients are impaired on tests of visual
attention is consistent with the neuropathology of this disease. PD is primarily characterized by degeneration of the substantia nigra within the basal ganglia (Agid, 1991; Albin, Young, & Penney, 1989; Gibb, 1991), and it is possible that these regions play an important role in attentional processes. In a recent study with normal subjects, positron emission tomography (PET) implicated the basal ganglia in selective attention processes (Corbetta, Miezin, Dobmeyer, Shulman, & Petersen, 1991). Additionally, past research with animals also emphasizes the role of the basal ganglia in attention functions (Apicella, Legallet, Nicoullon, & Trouche, 1991; Hassler, 1978; Rolls, Thorpe, Boytim, Szabo, & Perrett, 1984; Schneider, 1987). These results suggest that dysfunction within the basal ganglia may lead to impaired attentional functions in patients with PD (also see Jackson & Houghton, 1995). However, this is not the only possible neuroanatomical correlate of PD patients' attentional deficits. It is well known that the basal ganglia contain a large number of efferent and afferent connections (Alexander, DeLong, & Strick, 1986; Cummings, 1993), and it may be that dysfunction in other brain regions underlies PD patients' attentional deficits. Specifically, damage to either the frontal lobes or the superior colliculus can result in overt attentional impairment (Chevalier & Deniau, 1987; Corbetta et al., 1991; Guitton, Buchtel, & Douglas, 1985; Henik, Rafal, & Rhodes, 1994; Knight, 1984; Rafal, Posner, Friedman, Inhoff, & Bernstein, 1988), and given that the basal ganglia are connected to these regions, the attentional deficits exhibited by PD patients may be a result of deafferentation into these other brain areas. Thus, it may be that dysfunction of the subcortical structures and/or the secondary involvement of the frontal lobes and superior colliculus may be the neuropathological corollary of attentional deficits in PD patients.

Although attentional deficits have been observed in patients with PD, the exact nature of their impairments on such tasks has not been fully explored. Furthermore, not all studies have identified an attentional impairment in patients with PD (Brown & Marsden, 1988; Rafal, Posner, Walker, & Friedrich, 1984). One possible explanation for these discrepant findings may be that only a subgroup of PD patients demonstrated deficits on these tasks, and averaging participants' data may have obscured the finding of any group differences. It is well known that PD is not a homogeneous disease in which the cognitive functions of all patients are affected equally (Pirozzolo, Hansch, Mortimer, Webster, & Kuskowski, 1982; Rajput, Offord, Beard, & Kurland, 1984). On the basis of the variability of the pattern of clinical deficits in PD patients, several investigators have argued for the existence of subgroups of PD patients (Dubois, Boller, & Agid, 1991; Mayeux & Stern, 1983). However, the majority of studies that examined visual perception and attention in patients with PD have not taken this variation into consideration. Thus, the use of statistical techniques that rely on the averaging of participants' performances (e.g., analysis of variance) may have obscured important group differences at the individual subject level in these past studies.

In recent years, cognitive science research has increased empirical understanding of visual attention processes in normal individuals to the point where unified theoretical approaches to attention have been developed and tested through quantitative model-based analyses (e.g., Ashby, Prinzmetal, Ivry, & Maddox, 1996; Estes, 1994; Gossberg, Mingolla, & Ross, 1994; Maddox, Prinzmetal, Ivry, & Ashby, 1994; Maddox & Ashby, 1993, in press; Nosofsky, 1992; Reeves & Spelke, 1986). Model-based analyses are often better than analytic techniques relying on measures of central tendency for several reasons. First, model-based analyses enable researchers to investigate cognitive processes at the individual subject level. The fact that PD is not a homogeneous disease makes individual subject analyses particularly advantageous. Second, model-based analyses allows for a much finer grained analysis of an individual subject's performance. For example, model-based analyses allow us to distinguish a subject who can attend selectively from one who is unable to ignore an irrelevant stimulus dimension—that is, one who shows a selective attention deficit. Perhaps more importantly, the model-based analyses allow us to determine the magnitude of an attention deficit.

The present study utilized the perceptual categorization task (also called the general recognition categorization technique; Ashby & Gott, 1988; Ashby & Maddox, 1990, 1992; Maddox, 1995) to investigate attentional functioning in a group of PD patients without dementia and a group of age- and education-matched controls. In a typical perceptual categorization task, the experimenter defines two categories of stimuli (more frequently referred to as exemplars). In this experiment, the exemplars varied along two stimulus dimensions, horizontal line length and vertical line length. The participants were tested in three different experimental conditions: (a) dimensional integration, (b) selective attention, and (c) baseline.

In the dimensional integration condition, we constructed a situation in which an accurate categorization response required the participant to attend to both stimulus dimensions (i.e., both the horizontal and the vertical line). Figure 1a shows a subset of the category exemplars. All of the exemplars consisted of a horizontal and vertical line segment connected at the upper left. Exemplars from Category 1 usually contained a vertical line segment that was longer than the horizontal line segment, whereas the exemplars from Category 2 usually contained a vertical line segment that was shorter than the horizontal line segment. In this condition, the correct response required that the participant compare the lengths of the vertical and horizontal line segments. If the vertical line segment was longer than the horizontal line segment, then the participant was to respond “1.” Otherwise the participant was to respond “2.” This decision rule is displayed visually on the two-dimensional graph in the right-hand portion of Figure 1a. The x axis represents the horizontal line length, and the y axis the vertical line length. The optimal decision rule is expressed as a linear function of the horizontal and vertical line lengths, with a slope of one and an intercept of zero (represented by the broken line in Figure 1a). This is called the optimal decision bound. Optimal decision bounds are those that enable the participant to categorize the stimuli with the highest degree of accuracy (e.g., Maddox & Ashby, 1993).

In the selective attention condition, participants were required to base their decisions on only one stimulus dimension (either the horizontal or vertical line length). Thus, the optimal decision rule required that the participant attend to
one stimulus dimension and ignore the other. An example in which the vertical line was relevant is presented in Figure 1b. The exemplars from Category 1 usually contained a short vertical line but differed greatly in horizontal line length. On the other hand, the exemplars from Category 2 usually contained a long vertical line but differed greatly in horizontal line length. To respond optimally, the participant had to ignore the horizontal line segment and set a criterion, which we call \( V_{\text{crit}} \), along the vertical length continuum. All exemplars with a vertical length that was shorter than \( V_{\text{crit}} \) were categorized as a 1, and those exemplars with a vertical length that was longer than \( V_{\text{crit}} \) were categorized as a 2. This is a selective attention rule because, even though there is variation in the horizontal line length, this trial-by-trial variation is uninformative and should be ignored. Accurate categorization required the participant to attend to the length of only one line. The optimal decision bound when participants were told to focus on only the vertical line is expressed as a line with a zero slope and an intercept equal to the criterion value, \( V_{\text{crit}} \), as shown in the right-hand portion of Figure 1b (represented by the broken line).
In the baseline condition, the optimal decision bound was the same as in the selective attention condition; however, only the relevant stimulus dimension was presented in the display. Thus, \( V_{\text{opt}} \) was the same for the selective attention and the baseline conditions. An example in which the vertical line was relevant is presented in Figure 1c.

Quantitative models that were developed to account for normal participants responding (Maddox, 1995; Maddox & Ashby, 1993) were then applied to each individual's data in order to examine performance in the three experimental conditions. First, for each experimental condition, three different models were applied to each of the participant's data sets (see Modeling Approach below for more details). The optimal responding model examined whether the participant responded in an optimal manner given the requirements of the task in each of the specific conditions. The suboptimal responding model examined whether the participant performed according to the task requirements, but in a suboptimal manner (e.g., the participant attended selectively to the relevant component in the selective attention condition in a less efficient manner, yet still used a selective attention rule when performing the task). The deficit in responding model examined whether the participant did not perform according to the task requirements (e.g., the participant integrated information from the two stimulus components in the selective attention condition when the participant should have attended selectively to the relevant component and ignored the irrelevant component). Next, the fit of the models was compared, and the model that provided the best account of the data was chosen as the correct model (for details of this procedure see the Modeling Approach section and the Appendix). Fourth, chi-square tests were performed to determine whether the optimal, suboptimal, and deficit in responding frequencies differed across populations. If the PD patients demonstrated deficits, as compared with normal controls, then there should be a disproportionate number of data sets of PD patients that were best accounted for by the deficit in responding model. In contrast, if PD patients are not impaired, then there should not be a disproportionate number of data sets of PD patients accounted for by the deficit in responding model.

On the basis of the previous studies that have identified selective attention deficits in patients with PD, we predicted that the deficit in responding model would account for a disproportionate number of PD patients' data in the selective attention condition, as compared with normal controls. In contrast, we predicted no difference in the frequency distributions for the PD and normal controls in the dimensional integration and baseline conditions. This pattern of results suggest that patients with PD are impaired on tasks of visual selective attention.

Method

Participants

Seventeen patients with idiopathic PD without dementia (14 men and 3 women) and 17 normal controls (14 men and 3 women) participated in this study. The diagnosis of PD was made by a senior staff neurologist. PD patients with a history of stroke, head injury (loss of consciousness for more than 1 min), alcoholism (four or more drinks per day for more than 1 year), or serious psychiatric illness (major affective disorder or schizophrenia) were excluded from the study. The PD patients had been diagnosed with the disease for a mean of 12.7 years prior to their participation in this study. At the time of testing, 15 of the PD patients were taking dopaminergic medication, 1 patient was taking both dopaminergic and anticholinergic medication, and 1 patient was not taking any medication. According to Hoehn and Yahr's (1967) scale of motor impairment severity, 1 patient was in stage 1 of the disease (least impaired), 7 patients were in stage II, 6 in stage III, and 3 in stage IV (most impaired). Of the 17 PD patients who participated in this study, 12 had tremor as their predominant symptom.

The controls were recruited from the community, and exclusion criteria included a history of alcoholism, psychiatric illness, cerebral vascular accident, head trauma, or other significant neurological conditions. Controls were selected for inclusion in this study if their age and education levels were comparable to those of the PD patients. Table 1 shows the mean age, years of education, and scores on the Dementia Rating Scale (DRS; Mattis, 1976) for the PD patients and controls. The PD patients did not differ from the normal controls in terms of their mean age \((p > .10)\), years of education \((p > .70)\), or their scores on the DRS \((p > .08)\).

Stimuli and Stimulus Generation

In this study, the participants were presented with vertical and horizontal line segments of various lengths in three experimental conditions and were asked to categorize these stimuli on the basis of the lengths of the lines. Figure 1 presents examples of the stimuli. The stimuli were generated and presented in black on a white background with a Macintosh SE computer. In all three of the experimental conditions, two categories of stimuli (Category 1 and Category 2) were created by defining specific bivariate normal distributions. The stimuli were generated on each trial with the following procedure. First, a category was chosen at random. Next a random sample was taken from the appropriate category distribution. This specified an ordered pair \((x, y)\). This ordered pair was used to construct a stimulus with horizontal length, \(x\), and vertical length, \(y\). In each experimental condition, the optimal classifier predicted 95% accuracy. That is, a participant responding perfectly on every trial could achieve a maximum of 95% accuracy. This is due to the fact that the normal distributions used to construct the stimulus groups in this study overlap. Thus, a stimulus from Category 1 could be identical to a stimulus from Category 2. It has been argued that the normal distribution provides a good model of natural categories and thus experimental paradigms that utilize normally distributed categories have higher ecological validity (Ashby, 1992a; Flannagan, Fried, & Holroyd, 1986; Fried & Holroyd, 1984; Maddox & Ashby, 1993). Table 2

Table 1

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>PD ((n = 17))</th>
<th>Controls ((n = 17))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (SD)</td>
<td>65.41</td>
<td>69.12</td>
</tr>
<tr>
<td></td>
<td>8.11</td>
<td>6.70</td>
</tr>
<tr>
<td>Range</td>
<td>54–77</td>
<td>59–85</td>
</tr>
<tr>
<td>Education (SD)</td>
<td>15.85</td>
<td>15.35</td>
</tr>
<tr>
<td></td>
<td>2.32</td>
<td>2.15</td>
</tr>
<tr>
<td>Range</td>
<td>12–19</td>
<td>12–20</td>
</tr>
<tr>
<td>DRS (SD)</td>
<td>139.29</td>
<td>141.29</td>
</tr>
<tr>
<td></td>
<td>5.01</td>
<td>2.52</td>
</tr>
<tr>
<td>Range</td>
<td>126–141</td>
<td>134–144</td>
</tr>
</tbody>
</table>
Table 2  
Parameter Values (in Pixels) for the Category Populations (1 and 2) by Condition

<table>
<thead>
<tr>
<th>Value</th>
<th>Dimensional integration</th>
<th>Selective attention</th>
<th>Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Horiz. length (M) $\mu_M$</td>
<td>140</td>
<td>100</td>
<td>85</td>
</tr>
<tr>
<td>Vert. length (M) $\mu_V$</td>
<td>100</td>
<td>140</td>
<td>100</td>
</tr>
<tr>
<td>Variance for horizontal $\sigma^2$</td>
<td>92</td>
<td>92</td>
<td>92</td>
</tr>
<tr>
<td>Variance for vertical $\sigma^2$</td>
<td>92</td>
<td>92</td>
<td>92</td>
</tr>
<tr>
<td>Correlation between $\mu_M$ and $\mu_V$</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note. Parameter values for the selective attention and baseline conditions are for the condition in which the vertical line segment is relevant. Parameter values for the condition in which the horizontal line is relevant are obtained by switching the $\mu_M$ and $\mu_V$ values.

gives the exact parameter values describing the populations in each experimental condition. The lines in each of the conditions were 11 pixels thick.

Procedure

In this study, the participants were asked to categorize the visual stimuli in three different experimental conditions. At the start of each experimental condition, the participants were given extensive instructions that included the correct categorization rule (see below). In addition, a card was displayed above the computer screen throughout the experiment. It depicted prototypical stimuli from each of the two categories. The participants were given 15 practice trials prior to each experimental condition. If during the practice trials they committed three errors in a row, the examiner reread the instructions and reoriented them to the sign that depicted the prototypes. This procedure was included to ensure that all participants understood the instructions.

At the beginning of each practice and experimental trial, a small fixation square (57 x 57 pixels) appeared in the center of the screen. The stimulus appeared 500 ms later. The task was to determine the category membership and to respond by pressing the appropriate key. Corrective feedback was provided for 1 s following the participants’ response. Once the feedback was complete, the next trial was initiated by the examiner. Each participant took part in three experimental conditions, and the order of administration of the conditions was counterbalanced across subjects. To minimize using the categorization rule from the previous condition on any subsequent conditions, participants were administered a non-visual-perceptual task between each of the three experimental conditions. The time between each experimental condition was approximately 35 min.

Dimensional integration condition. In this condition, accurate responding required the use of information from both stimulus dimensions (i.e., the horizontal and vertical line) in order to correctly classify the stimuli. Thus, the participants needed to integrate information from the two dimensions. They were told to press one computer key if the horizontal line was longer than the vertical line (Category 1 stimuli) and another key if the vertical line was longer than the horizontal line (Category 2 stimuli). One hundred trials were administered in this condition and were preceded by 15 practice trials.

Selective attention condition. In this condition, the participants were administered two separate blocks of trials: one block in which the horizontal line was relevant and another block in which the vertical line was relevant. The participant needed to attend to only one stimulus dimension in order to correctly classify the stimuli. Participants were asked to ignore the other stimulus dimension, although it varied in length on each trial. Thus, the participants needed to attend selectively to one dimension and ignore the other. They were told to press one computer key if the relevant visual dimension was short (Category 1 stimuli) and another key if the relevant dimension was long (Category 2 stimuli). Each block consisted of 60 trials and were preceded by 15 practice trials, for a total of 120 experimental trials and 30 practice trials. The stimuli in which the relevant visual dimension was less than 128 pixels should have been classified as short, and the stimuli in which the relevant dimension was greater than 128 pixels should have been classified as long.

Baseline condition. This condition was identical to the selective attention condition, except that the irrelevant dimension was absent from the display. In one block of trials, the participants were presented with horizontal lines, and in the other block they were presented with vertical lines. Each block in this condition consisted of 60 trials and were preceded by 15 practice trials, for a total of 120 experimental trials and 30 practice trials for this condition.

Modeling Approach

To investigate participants’ attention abilities, a series of mathematical models was applied to each participant’s data. Maddox and Ashby (1993; Ashby, 1992a; Maddox, 1995) developed these models specifically for analyzing data collected in the perceptual categorization task. The models assume that the participant partitions the stimulus space into two response regions. Response 1 is given to stimuli that fall in one region, and Response 2 is given to stimuli that fall in the other region. The partition between the two response regions is called the decision bound. Versions of the decision bound model differ only in the type of decision bound that the participant is assumed to use. This article considers the following three decision bound models: (a) the optimal decision bound model (hereafter referred to as the optimal model), (b) the suboptimal dimensional integration model; and (c) the suboptimal selective attention model. The optimal model assumes that the participant used the decision bound that maximizes categorization accuracy (i.e., the experimenter-defined decision bound). The suboptimal dimensional integration model assumed that the participant used some linear dimensional integration decision bound that differs from the optimal decision bound, whereas the suboptimal selective attention model assumes that the participant used a selective attention bound, but one that differs from the optimal bound.

The three models differ in their generalization (or flexibility). The optimal model is the most constrained (or least flexible) model because the slope and intercept of the decision bound are determined by the experimental condition, that is, the slope and intercept are fixed. The suboptimal dimensional integration model is the most general model because the slope and intercept of the decision bound are free parameters that are estimated from the data (i.e., the slope and intercept are those values that best separate the participant’s 1 and 2 responses). The suboptimal selective attention model is intermediate in generality. In this model, the slope is fixed at zero, but the intercept is a free parameter that is estimated from the data. These
models are “nested” in the sense that a more constrained model can be derived from a more general model by holding constant some of the free parameters of the general model. For example, the suboptimal selective attention model can be derived from the suboptimal dimensional integration model by setting the slope parameter of the suboptimal dimensional integration model to zero. Analogously, the optimal selective attention model can be derived from the suboptimal selective attention model by setting the intercept to \( V_{\text{opt}} \).

Because the models are nested, the suboptimal dimensional integration model can never be outperformed (on the basis of the absolute fit) by the suboptimal selective attention or optimal dimensional integration model. Similarly, the suboptimal selective attention model cannot be outperformed by the optimal selective attention model. Thus, the suboptimal dimensional integration model will always provide the best fit of the data, and the optimal model will always provide the worst fit of the data. The law of parsimony states that the goal should be to identify the simplest explanation of the data, that is, the goal should be to identify the model with the fewest free parameters that adequately describes the data. Statistical methods for achieving this goal are well established and are based on statistics derived from the well-known chi-square distribution. The basic approach is to compare the fit values for two models, such as the optimal selective attention model and the suboptimal selective attention model. The suboptimal selective attention model must provide a better absolute fit, but the improvement in fit may not be statistically significant. If the improvement in fit for the more general model (the suboptimal selective attention model, in this example) is not statistically significant, then the more restricted model (the optimal selective attention model, in this example) is assumed to provide the most accurate description of the data. We call this the model that provides the “most parsimonious” account of the data. The details of the statistical method and a concrete example are provided in the Appendix and in previous work (e.g., Ashby, 1992b; Wickens, 1982).

Optimal responding: This modeling approach addresses three important issues. First, the model-based analyses allowed us to determine whether the participant’s performance was optimal. That is, did the participant use the categorization rule defined by the experimenter? In the dimensional integration condition, the optimal decision bound had a unit slope and a zero intercept, as represented by the dashed line in Figure 1a. If a participant used this decision bound to determine categorization judgments, then the optimal model would provide the most parsimonious account of the participant’s data. That is, most of the participant’s responses would fall above the dashed line, and most of the 2 responses would fall below it. Similarly, in the selective attention and baseline conditions, the optimal decision bound had a slope of zero and an intercept of \( V_{\text{opt}} \), as represented by the dashed line in Figure 1b and 1c. If a participant used this decision bound to determine their categorization responses, then the optimal model would provide the most parsimonious account of the data. Again, most of the participant’s responses would fall below the dashed line, and most of the 2 responses would fall above it.

Suboptimal responding: Second, the model-based analyses allowed us to determine whether the participant was able to: (a) integrate information from the two stimulus dimensions in the dimensional integration condition, but at a suboptimal level, and (b) attend selectively to the relevant stimulus dimension in the selective attention condition, but at a suboptimal level. The suboptimal dimensional integration model assumed that the participant integrated information from the two dimensions (i.e., compared the two line segment lengths), but used a decision bound with something other than a unit slope and zero intercept. The suboptimal selective attention model assumed that the participant attended selectively to one stimulus dimension and ignored the other, but applied a criterion other than \( V_{\text{opt}} \) along the relevant stimulus dimension.

Deficits in responding: Third, the model-based analyses allowed us to determine whether the participant showed deficits in dimensional integration or selective attention abilities. For example, the participant may be unable to attend to both line segments in the dimensional integration condition. This participant might completely ignore information about the horizontal line length and attend only to the vertical line length. This participant would be classified as showing a deficit in dimensional integration. Now consider a situation in which the participant is unable to ignore the irrelevant line segment in the selective attention condition. This participant might integrate information from the two line segments when asked to make a categorization judgment. This participant would be classified as showing a deficit in selective attention.

Distinguishing suboptimal responding from deficits in dimensional integration or deficits in selective attention: One of the main goals of this research was to distinguish participants who showed deficits in dimensional integration or selective attention from those who responded suboptimally. This is an extremely important distinction that is impossible to make on the basis of percentage correct analyses (at least in the present experimental paradigm). The reasoning is as follows: Consider a selective attention condition in which an individual could achieve 95% accuracy when using the optimal decision bound. What if, instead of achieving 95% accuracy, a participant achieved 85% accuracy? What conclusions could be drawn about this person’s ability to attend selectively? On the basis of percentage correct only, it is not possible to distinguish a participant who used a suboptimal selective attention rule from one who was unable to attend selectively (i.e., showed a selective attention deficit). This is the case because there exists at least one suboptimal selective attention rule, as well as at least one deficit in selective attention rule that would yield 85% accuracy. The problem with using percentage correct performance is that it is based on the participant’s performance averaged across experimental trials. (Of course, this is implicit in the percentage correct statistic.) Because our goal was to identify participants with selective attention deficits, we needed a technique that would allow us to distinguish an individual who could attend selectively (albeit at a suboptimal level) from an individual who could not. The model-based analyses solved this problem by estimating the slope and intercept of a stable linear decision boundary that most accurately described the nature of each participant’s distribution of responses. When the estimated slope was zero, we inferred an ability to attend selectively. When the slope was nonzero, we inferred a deficit in selective attention. The amount of deviation from a zero slope also allowed a rough estimate of the magnitude of the selective attention deficit.

When applying the models we used a maximum likelihood criterion to estimate the slope and intercept of the best fitting decision bound (see Appendix). Maximum likelihood criteria have several important

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1. Actually, these are the parameters of the optimal bound in the selective attention and baseline conditions in which the vertical dimension was relevant. When the horizontal line was relevant in these two conditions, the optimal rule was to set a criterion along the horizontal dimension and to ignore the vertical dimension. This is equivalent to using a decision bound with a slope of infinity. Without loss of generality and for ease of comparison, when applying the decision bound models to data for which the horizontal dimension was relevant, we first interchanged the horizontal and vertical coordinate values for each experimental trial. Under these conditions, the resulting optimal decision bound was identical to that when the vertical dimension was relevant.

2. If the participant were to use a decision bound with a zero slope, this would not be considered suboptimal dimensional integration because a slope of zero implies selective attention.
statistical properties (see Ashby, 1992b; Wickens, 1982). In essence, the maximum likelihood procedure attempts to maximize the fit of the model to the data. By fit we simply mean that this procedure attempts to generate predictions from the model that most closely match the observed data. Our data were simply the participant’s categorization responses for each presented exemplar. Thus, for each exemplar, the observed probability of responding Category 1 was either 1 or 0. For a fixed decision bound, the model generated a predicted probability of responding Category 1 for each exemplar. Using the maximum likelihood criterion, we simply adjusted the decision bound slope and intercept until the difference between the observed and predicted Category 1 response probabilities was minimized. The likelihood ratio tests were used to determine the model that provided the most parsimonious account of each participant’s data in the three conditions.

Results

Mean Accuracy

Although we have just argued against the validity of the percentage correct statistic as a means of identifying selective attention deficits, it is instructive to perform these analyses for two reasons. First, this is the most common method of data analysis, and it allows us to compare our results with previous research. Second, and perhaps more importantly, it allows us to compare the results of average participant analyses on the basis of the percentage correct statistic, with the more sensitive single participant analyses on the basis of the nature of their error distributions. Table 3 displays the accuracy rates for all three conditions averaged across participants.

The only condition in which the performance of PD patients differed significantly from that of the normal controls was in the selective attention condition (p < .05). In this case, the PD patients were significantly less accurate than the normal controls. What does this result tell us about their ability to attend selectively? A critical point that we wish to make in this article is that a statistically significant difference in accuracy, on the basis of data collapsed across subjects and trials, reveals little about the underlying selective attention abilities of our PD patients. We only know that PD patients were less accurate (on average). What this does not reveal is what pattern of responding led to the reduction in accuracy.

The important distinction here is between a pattern of responding in which the participant accurately ignores the irrelevant dimension (i.e., a participant who attends selectively) and one in which the participant is unable to ignore the irrelevant dimension (i.e., a participant who shows a deficit in selective attention). However, there are two types of selective attention rules: optimal and suboptimal. The optimal selective attention rule is the one defined by the experimenter. A suboptimal selective attention rule is any other rule in which the irrelevant dimension is ignored. A participant using a suboptimal selective attention rule will show a reduced accuracy rate, just like a participant showing a deficit in selective attention. Thus, on the basis of accuracy alone, it is impossible to distinguish suboptimal selective attention from deficits in selective attention. On the other hand, the model-based analyses allow us to rigorously discriminate (on the basis of well-established statistical criterion) between these three different patterns of responding: optimal selective attention, suboptimal selective attention, and deficits in selective attention.

Quantitative Model-Based Analyses

The three decision bound models were fit to the data from each participant in each experimental condition. A detailed description of the model fitting and testing procedures is outlined in the Appendix.

Dimensional integration condition. As stated above, the first step in the model-based analyses was to determine the model that provided the most parsimonious account of the data. This was defined as the model with the fewest free parameters whose fit was not significantly improved on by a more general model. The details of this procedure are outlined in the Appendix; however, a graphic description of this process is displayed for a representative PD patient in Figure 2. The top portion of the figure depicts the participant’s pattern of 1 and 2 responses. The best fitting decision bound from the optimal dimensional integration, the suboptimal dimensional integration, and the deficit in dimensional integration models are displayed in the center portion of the figure along with the participant’s responses. Recall that the suboptimal dimensional integration model is the most general model and thus must provide the best absolute fit of the data. However, it may not provide the most parsimonious account of the data, that is, a significant improvement in fit over the optimal dimensional integration model or the deficit in dimensional integration model. In Figure 2, the improvement in fit for the suboptimal dimensional integration model is statistically significant and thus for this participant, the suboptimal dimensional integration model provides the most parsimonious account of the data.

Once we identified the model that provided the most parsimonious account of the data for each participant, each participant was classified into either the optimal dimensional integration (O-DI), the suboptimal dimensional integration (SO-DI), or the dimensional integration deficit (D-DI) group.

Table 3

<table>
<thead>
<tr>
<th>Condition</th>
<th>PD</th>
<th>Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimensional integration</td>
<td>88</td>
<td>90</td>
</tr>
<tr>
<td>Selective attention</td>
<td>81</td>
<td>85*</td>
</tr>
<tr>
<td>Selective attention baseline</td>
<td>85</td>
<td>86</td>
</tr>
</tbody>
</table>

Note: PD = Parkinson’s disease.

*p < .05.

3 We are not arguing that traditional analyses on the basis of accuracy data are always equivocal with respect to diagnosing deficits in selective attention, although we do argue that many commonly used tasks are equivocal. However, the perceptual categorization task does suffer from this weakness. Fortunately, the model-based analyses overcome this potential weakness and took full advantage of the many positive aspects of this task.
MODELS

O-DI

SO-DI

D-DI

Most Parsimonious Account

SO-DI
The percentage of participants classified into each of these groups by population is displayed in Table 4.

Table 4 shows that a large proportion of the PD patients (12 of 17; 70.58%) and controls (10 of 17; 58.82%) accurately applied the optimal decision bound, that is, the optimal dimensional integration model provided the most parsimonious account of the data. The remaining subjects from both populations utilized a suboptimal dimensional integration rule. None of the PD patients or controls showed a deficit in dimensional integration. Thus, when required to integrate information from two stimulus dimensions, both the PD patients and controls were able to accomplish this goal, although some were unable to integrate information in an optimal fashion. To determine whether there was a disproportionate number of PD patients who responded optimally, we performed a chi-square test in which population (PD vs. control) and dimensional integration group (O-DI vs. SO-DI) served as the cells. This analysis suggested no significant difference in the frequency of PD patients and controls who were classified as optimal or suboptimal responders; χ²(1, N = 34) = 1.15, p > .25. In summary, the model-based analyses suggest that (a) all PD patients were able to integrate information from the two stimulus dimensions when this was required, albeit in a suboptimal fashion for some of the patients, (b) a large proportion of PD patients were able to integrate information in an optimal fashion, and this proportion did not differ from the proportion observed for the age- and education-matched normal controls, and (c) PD patients and controls evidenced no deficits in dimensional integration ability.

A plot of the response data, along with the decision bound for the best fitting model, for a representative optimal and suboptimal PD patient are presented in Figure 3. Figure 3a contains data from a PD patient whose data were best fit by the optimal dimensional integration model. Figure 3b contains data from a PD patient whose data were best fit by the suboptimal dimensional integration model. In Figure 3b, the best fitting decision bound accurately characterizes the participant’s responses and is steeper than the optimal decision bound.

Selective attention condition. Again, all three models were applied to the data from each participant. Because the selective attention condition consisted of two blocks of trials (one block when the vertical line was relevant and another block when the horizontal line was relevant), each participant contributed two data sets to these analyses. Once we identified the model that provided the most parsimonious account of each data set, each data set was classified into the optimal selective attention (O-SA), the suboptimal selective attention (SO-SA), or the selective attention deficit (D-SA) group. A graphic description of our model classification approach is depicted in Figures 4 and 5. Figure 4 displays the data from a representative PD patient who was classified as showing a deficit in selective attention. Figure 5 displays the data from a representative PD patient who was able to attend selectively, but used a selective attention rule that was suboptimal.

Several aspects of the selective attention condition analyses are of interest. First, there was a decrease in the proportion of PD patients and controls’ data sets that suggested optimal responding in the selective attention condition, as compared with the dimensional integration condition. The decrease was much larger for the PD patients (PD: 38.23%; controls: 8.82%). Clearly, participants, especially the PD patients, found the selective attention task more difficult. Even so, the fact that 32.35% of our PD data sets suggested optimal selective attention is quite impressive. Second, although the proportion of PD patients and controls who responded optimally was lower in the selective attention condition, the number of PD patients and controls who responded optimally did not differ significantly. This was assessed by performing a chi-square test in which population (PD vs. control) and selective attention group (O-SA vs. SO-SA/D-SA) served as the cells: χ²(1, N = 68) = 2.186, p > .10.

Third, approximately one third of the PD patients (11 of 34; 32.35%) and controls (12 of 34; 35.29%) data sets suggested suboptimal selective attention. In other words, in these cases, the participant was able to ignore the irrelevant dimension (i.e., attend selectively) but did not use the optimal criterion when making judgments about the length of the relevant dimension. An examination of the best fitting criterion for these participants suggested that both the controls and PD patients used a criterion that was smaller than the optimal criterion. The optimal criterion was 128 pixels. Thus any stimulus with a horizontal length (or vertical length depending on the condition) less than 128 pixels should receive response 1, and any stimulus with a length greater than 128 should receive response 2. The best fitting criterion (averaged across

Table 4

<table>
<thead>
<tr>
<th>Population</th>
<th>O-DI</th>
<th>SO-DI</th>
<th>D-DI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parkinson’s disease</td>
<td>70.58</td>
<td>29.41</td>
<td>0</td>
</tr>
<tr>
<td>Control</td>
<td>58.82</td>
<td>41.12</td>
<td>0</td>
</tr>
</tbody>
</table>

The dimensional integration deficit group was left out of this analysis because none of the participants in either group showed a dimensional integration deficit.
Figure 3.  (a) Response data from a representative dimensional integration (DI) condition participant who was classified into the optimal (O) dimensional integration group. The solid line represents the optimal decision bound. (b) Response data from a representative dimensional integration condition participant who was classified into the suboptimal (SO) dimensional integration group. The solid line represents the best fitting decision bound. (c) Response data from a representative selective attention (SA) condition participant who was classified into the optimal selective attention group. The solid line represents the optimal decision bound. (d) Response data from a representative selective attention condition participant who was classified into the suboptimal selective attention group. The solid line represents the best fitting decision bound. (e) Response data from a representative selective attention condition participant who was classified into the selective attention deficit (D) group. The solid line represents the best fitting decision bound.
Figure 4. Graphic representation of the classification scheme used to determine the model that provides the most parsimonious account of the data, showing the selective attention (SA) condition data for a representative Parkinson's disease patient whose data were most parsimoniously accounted for by the selective attention deficit model. Square = 1 response; + = 2 response. O = optimal; SO = suboptimal; D = deficit.
Horizontal Length
(square = "1"; plus = "2")

MODELS

O–SA

SO–SA

D–SA

Most Parsimonious Account

SO–SA
Table 5
Percentage of Selective Condition Data Sets Classified Into Optimal Selective Attention (O-SA), Suboptimal Selective Attention (SO-SA), and Selective Attention Deficit (D-SA) Groups by Population

<table>
<thead>
<tr>
<th>Population</th>
<th>O-SA</th>
<th>SO-SA</th>
<th>D-SA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parkinson’s disease</td>
<td>32.35</td>
<td>32.35</td>
<td>35.29</td>
</tr>
<tr>
<td>Control</td>
<td>50.00</td>
<td>35.29</td>
<td>14.70</td>
</tr>
</tbody>
</table>

data sets) was 119 for the PD patients and 122 for the controls. Thus, both groups tended to use a criterion that was smaller than the optimal. One question that comes to mind immediately is whether participants naturally use a smaller than optimal criterion, or whether this is somehow caused by the presence of the irrelevant dimension. This issue is addressed below when the model-based analyses of the baseline conditions are presented.

Finally, and perhaps most importantly, a large proportion of the PD patients showed clear deficits in selective attention, that is, were unable to ignore the irrelevant dimension. Twelve of 34 (35.27%) PD data sets suggested selective attention deficits, whereas only 5 of 34 (14.70%) control data sets showed a similar selective attention deficit. To determine whether this selective attention deficit was significantly more frequent in the PD than the control sample, we performed a chi-square test with population (PD vs. control) and selective attention group (O-SA/SO-SA vs. D-SA) as the cells. The chi-square statistic was significant, suggesting the selective attention deficit was more frequent in the PD patients: \( \chi^2(1, N = 68) = 3.85, p < .05 \). This is termed an interference effect (e.g., Garner, 1974) because participants were unable to ignore the irrelevant dimension, that is, including the irrelevant dimension interfered with processing of the relevant dimension. What these data suggest is that a fairly large subgroup (35%) of our PD patients (and a small subgroup of the controls; 15%) evidenced a qualitatively different type of behavior from the other patients. Specifically, this subgroup of patients shows a clear deficit in selective attention. Although specifically instructed to ignore one stimulus dimension, these participants were unable to do so.

To gauge the magnitude of this deficit, that is, to quantitatively measure this deficit, we examined the best fitting slope and intercept parameters from the deficit in selective attention model (i.e., the suboptimal dimensional integration model) for this subgroup of patients. As suggested by these slope and intercept values, the degree of interference from the irrelevant dimension was nontrivial. The optimal categorization rule required the participant to ignore the irrelevant dimension and set a criterion of 128 pixels along the relevant dimension. As shown in Figure 1b, this translated into a decision bound with a slope of zero and an intercept of 128 pixels. After averaging the slope and intercept values from the subgroup of PD patients who showed a clear deficit in selective attention, we found the slope to be 0.62 and the intercept to be 56. A slope of 1 suggests that participants were allocating equal amounts of attention to both dimensions, and a slope between 0 and 1 suggests participants were allocating more attention to the relevant dimension. Thus, although these participants were allocating more attention to the relevant dimension, they were still allocating a considerable amount of attention to the irrelevant dimension.

Figures 3 (Panels c–e) presents the response data, along with the decision bound for a representative optimal selective attention, suboptimal selective attention, and selective attention deficit participant. For each participant, the best fitting decision bound accurately characterized the participant’s responses, that is, the best fitting decision bound divides the participant’s responses in such a way that nearly all the 1 responses are on one side of the bound, and nearly all the 2 responses are on the other side of the bound, with few mispredicted responses. The fact that the best fitting decision bound accurately partitioned the 1 and 2 responses will turn out to be critically important in rejecting a reasonable alternative explanation of our findings.

Baseline condition. Because the irrelevant component was absent from the display, only the optimal and suboptimal selective attention models were applied to the data from each participant. As with the selective attention condition, each participant contributed two data sets to this analysis because each participant took part in two blocks of trials in this condition (one block of trials when the vertical line was presented and another block when the horizontal line was presented). Once the model that provided the most parsimonious account of the data was identified for each data set, the data sets were classified into either the optimal or suboptimal group. The percentage of data sets classified into each of these groups by population is displayed in Table 6.

As in the dimensional integration condition, a large proportion of the PD (17 of 34; 50%) and control (24 of 34; 71%) data sets suggested optimal responding. However, as seen in other conditions, these differences were not statistically significant, although they approached significance; \( \chi^2(1, N = 68) = 3.01, p = .083 \). Thus, it appears that the differences in the proportion of PD patients who were impaired in the selective attention condition cannot easily be accounted for by the task demands per se. The task demands were exactly the same in the selective attention and baseline conditions, and the only difference between the two conditions was the presence of an irrelevant dimension in the selective attention condition. Therefore, the fact that a significantly larger proportion of PD patients evidenced a selective attention deficit was most likely due to the interference effects of the irrelevant stimulus dimension.

Figure 5 (opposite). Graphic representation of the classification scheme used to determine the model that provides the most parsimonious account of the data, showing the selective attention (SA) condition data for a representative Parkinson’s disease patient whose data were most parsimoniously accounted for by the suboptimal (SO) selective attention model. Square = 1 response; + = 2 response; O = optimal; D = deficit.
Table 6
Percentage of Baseline Condition Data Sets Classified Into the Optimal and Suboptimal Conditions by Population

<table>
<thead>
<tr>
<th>Population</th>
<th>Optimal</th>
<th>Suboptimal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parkinson’s disease</td>
<td>50.00</td>
<td>50.00</td>
</tr>
<tr>
<td>Control</td>
<td>70.59</td>
<td>29.41</td>
</tr>
</tbody>
</table>

When participants were required to attend selectively to the relevant dimension in the presence of an irrelevant stimulus dimension (i.e., in the selective attention condition), nearly one third of the PD patients and controls used a suboptimal selective attention rule. For both groups, the best fitting criterion value was smaller than the optimal criterion value. One possibility is that participants generally underestimate the optimal criterion, whereas another possibility is that this is due to the presence of the irrelevant dimension. To test these hypotheses, we examined the best fitting criterion value for those in the baseline condition who were classified into the suboptimal responding group. The best fitting criterion values (averaged across data sets) were 115 for the PD patients and 126 for the controls. As in the selective attention condition, these values are smaller than the optimal value of 128. Interestingly, the criterion value for the controls was closer to optimal when the irrelevant dimension was absent, whereas for the PD patients, the criterion value was closer to optimal when the irrelevant dimension was present. These results, although difficult to explain, suggest that in general participants may underestimate the optimal criterion and that this may occur to a greater extent in patients with PD when they are presented with competing perceptual information. Future research should examine the nature of this underestimation in both normal individuals and PD patients.

Alternative Explanations of the Observed Selective Attention Deficits

The results of the model-based analyses provide good evidence that a significant subgroup of our PD patients were unable to attend selectively even when explicitly instructed to do so. This conclusion is based on the superior fits of a model that assumed the participant integrated information from both dimensions in the selective attention condition. However, one must be cautious when using this sort of classification scheme because this model is also the most general model. In the case of a participant whose responding is erratic and is not well described by any single decision bound, it is very likely that none of the models under investigation would accurately account for the data; however, it is also very likely that the most general model would provide the most parsimonious account of the data. Thus, one possibility is that our PD patients who had been classified as showing a selective attention deficit were simply unable to use any single decision bound; instead, they switched bounds periodically throughout the experimental session.

To test this possibility, we computed the percentage of responses accounted for by the best fitting decision bound for participants classified into the optimal, suboptimal, and selective attention deficit groups. If the participants who were classified into the selective attention deficit group were responding in an erratic fashion, then the percentage of responses accounted for by the best fitting decision bound should be well below 100%. However, if these participants are showing a true selective attention deficit, then the percentage of responses accounted for by the best fitting decision bound should be quite high, in the range of 90%–100%. These values are displayed in Table 7 for the optimal selective attention, suboptimal selective attention, and selective attention deficit groups by participant population. For completeness, the analogous values from the dimensional integration and baseline conditions are also included in the table.

The following inferences can be drawn from an examination of Table 7. First, the data provide support for the conclusion that the PD patients and controls who were classified into the selective attention deficit group are in fact showing a true deficit in selective attention and are not simply responding in an erratic fashion. The best fitting decision bound accounted for 93.85% and 91.99% of the responses from these PD patients and controls, respectively. This finding suggests that these participants were unable to ignore the irrelevant stimulus dimension but were consistent in their use of a single decision bound. Second, the percentage of responses accounted for by the best fitting decision bound differs little across populations. Averaged across experimental conditions and best fitting models, the percentage of responses accounted for is 92.77% and 93.86% for the PD patients and controls, respectively. Finally, the percentage of responses accounted for was high in all cases (ranging from 89.66%–97.58%). Although several participants were unable to use the optimal categorization rule, whether it be an integration or selective attention rule, these results suggest that the rule used by each participant was used in a consistent manner. In other words, participants’ responding was not erratic because of the use of

Table 7
Percentage of Responses Accounted for by the Best Fitting Decision Bound for Participants Classified Into the Optimal, Suboptimal, and Deficit in Responding Groups (Averaged Across Participants) by Experimental Condition and Study Group

<table>
<thead>
<tr>
<th>Condition</th>
<th>Optimal PD</th>
<th>Optimal Control</th>
<th>Suboptimal PD</th>
<th>Suboptimal Control</th>
<th>Deficit PD</th>
<th>Deficit Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimensional integration</td>
<td>94.80</td>
<td>97.58</td>
<td>97.33</td>
<td>97.24</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Selective attention</td>
<td>89.67</td>
<td>90.85</td>
<td>89.66</td>
<td>92.79</td>
<td>93.85</td>
<td>91.99</td>
</tr>
<tr>
<td>Baseline</td>
<td>91.51</td>
<td>94.19</td>
<td>92.58</td>
<td>92.25</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. PD = Parkinson’s disease.
several different rules within each of the experimental conditions.

Another alternative explanation of our results has to do with the fact that the perceptual categorization task places heavy demands on visual-perceptual abilities. Although we went to great lengths to minimize demands on memory and problem-solving abilities, adequate visual perception is important for good performance in this task. Thus, it might be argued that the observed deficits in the PD patients in the selective attention condition are due to impaired visual perception and not a selective attention deficit per se. There are at least two arguments against this interpretation. First, as described above, although several participants were unable to attend selectively, the best fitting decision bound accurately accounted for over 90% of each participant's responses. If visual-perceptual abilities were poor, and the patients had a primary deficit in simply perceiving the stimulus components, then the data would most likely have appeared much more erratic than was observed. That is, participants' best fitting decision bounds in each of the conditions would have accounted for a lower percentage of the responses. Second, there did not appear to be any differences between the PD patients and controls in the dimensional integration condition. If visual-perceptual deficits could solely account for the pattern of our results, then PD patients should have been impaired in the dimensional integration condition as well. Participants were presented with the same type of stimuli (i.e., a horizontal and a vertical line) in the dimensional integration and selective attention conditions; the perceptual input for the two conditions was analogous. Therefore, the only difference between the two conditions was the nature of the attentional requirements of the tasks. In the dimensional integration condition, participants had to attend to both stimulus dimensions and integrate information from the two dimensions, whereas in the selective attention condition, participants had to ignore one dimension and attend to the other. The finding that PD patients were only impaired on the selective attention condition supports the notion that deficits in visual perceptual processes could not completely account for the differences between the PD patients and normal controls in this condition, but that the differences in the attentional demands of the tasks most likely resulted in the group differences.

A final alternative explanation of our results is that the observed selective attention deficit was due to the order in which participants were administered the selective attention and dimensional integration conditions. For example, if a PD patient was administered the selective attention condition first and took longer to adapt to the task in general, then this patient may have performed more poorly on the selective attention condition relative to the other conditions. Similarly, if a PD patient was administered the dimensional integration condition prior to the selective attention condition and the patient perseverated on the decision rule in the dimensional integration condition by continuing to apply this rule in the selective attention condition, this PD patient would also perform more poorly on the selective attention condition relative to the other conditions.

As outlined in the Procedure section, several steps were taken to minimize the possibility of order effects. Participants were given detailed task instructions, and practice trials were administered prior to each experimental condition. In addition, participants performed an unrelated task between each experimental condition. Although we are confident that these measures were successful, we decided to test explicitly for order effects. Specifically, we divided the PD patients into those who were administered the selective attention condition first versus those who were administered the dimensional integration condition first. Within these two groups, we computed the number of PD patients who displayed and who did not display a deficit in the selective attention condition. If order effects existed in our data, we would expect a disproportionate number of deficit and no-deficit patients in these two groups. The data suggested order effects were not present. Of those patients who were administered the selective attention condition first, 4 demonstrated a selective attention deficit and 3 did not. Similarly, of those patients who were administered the dimensional integration condition first, 5 demonstrated a selective attention deficit and 5 did not. A chi-square analysis indicated that the proportion of patients from each subgroup in each condition did not differ significantly (p > .05). Thus, it appears that order of administration was not associated with whether PD patients were impaired in the selective attention condition.

Subgroup Comparisons

One of the many advantages of this model-based approach is that we can perform single-subject analyses. By doing this, we were able to distinguish subgroups of PD patients who showed particular visual attention deficits from those who did not. This fine-grained classification of PD patients into subgroups allows us to determine whether these subgroups differ on any other cognitive abilities. To facilitate this comparison, we subdivided our PD patients into two groups: those who showed selective attention deficits (PD-D for deficit), and those who showed no selective attention deficits (PD-ND for no deficit). Those PD patients whose data from either of the two blocks of trials in the selective attention condition suggested a selective attention deficit were classified into the PD-D subgroup. The remaining patients (i.e., those in the optimal or suboptimal group) were classified into the PD-ND subgroup.

This scheme classified 10 patients into the PD-D and 7 patients into the PD-ND subgroup. The two PD subgroups were not significantly different in age or education (p > .05 for both comparisons), although the PD-D patients tended to be older (M = 67.80 for the PD-D subgroup and M = 62.00 for the PD-ND subgroup). Then we compared the DRS scores for these two subgroups of patients. These results are summarized in Table 8. A comparison between the total DRS scores of the PD-D and PD-ND patients indicated that the two groups did not differ in their global level of cognitive functioning (p > .05). However, an examination of the individual subscales of the DRS revealed that the PD-D patients had significantly lower scores on the conceptualization subtests, t(15) = 2.85, p < .05, which measures abstract reasoning. In contrast, the two groups did not differ significantly on any of the other subscales that include measures of general attention, memory, initiation and perseveration, and visual construction (p > .05 for all comparisons).
Table 8

Dementia Rating Scale (DRS) Scores for the Two Parkinson's Disease (PD) Subgroups

<table>
<thead>
<tr>
<th>PD subgroup</th>
<th>With deficit</th>
<th>Without deficit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Attention</td>
<td>36.30</td>
<td>0.38</td>
</tr>
<tr>
<td>Memory</td>
<td>24.30</td>
<td>1.49</td>
</tr>
<tr>
<td>Construction</td>
<td>5.70</td>
<td>0.48</td>
</tr>
<tr>
<td>Conceptualization</td>
<td>36.10</td>
<td>0.95</td>
</tr>
<tr>
<td>Initiation/Perseveration</td>
<td>35.30</td>
<td>2.63</td>
</tr>
<tr>
<td>DRS total</td>
<td>137.70</td>
<td>5.38</td>
</tr>
</tbody>
</table>

\*p < .05.
\*\*= 10.
\*\*\*= 7.

Although these subgroup comparisons did not yield any striking subgroup differences, clearly the approach was promising. In future work, we plan to collect data from a much wider range of clinical measures in order to better understand and identify differences in behavior among the various subgroups of PD.

**Discussion**

Past research suggests that PD patients are impaired on tasks of visual perception. However, much of this research is controversial because many of the tasks used to demonstrate visual perceptual impairment in PD patients place heavy demands on other cognitive functions, such as memory and problem solving, and as a result, deficits of PD patients on these tasks may be related to impairment in other aspects of cognition. In addition, much of this work fails to take a component process approach to the study of visual perceptual performance. In the present study, a group of PD patients without dementia who were age and education matched participated in a series of perceptual categorization tasks. The task placed minimal demands on memory and problem-solving abilities and allowed us to test specific components of attentional processing through manipulation of the categorization rule that maximizes categorization accuracy. In addition, quantitative model-based analyses were performed that allowed us to identify subgroups of PD patients with selective attention deficits and allowed us to quantify the magnitude of these deficits.

Each participant completed three unique conditions. In the dimensional integration condition, the optimal categorization rule required the participant to attend to both stimulus dimensions and weight information about each dimension equally when making a correct categorization response. In the selective attention condition, the participant was required to set a criterion along one stimulus dimension and ignore irrelevant variation along the other dimension. In the baseline condition, the participant was required to set a criterion along one stimulus dimension while the other stimulus dimension was absent from the display.

Taken together, the results of the model-based analyses can be summarized as follows. First, PD patients and normal controls showed no deficits in dimensional integration. In fact, a majority of the individuals in each population used the optimal decision bound. Second, in the baseline condition in which the irrelevant dimension was absent from the display, there was again no significant difference in performance between the PD patients and the normal controls, and a majority of the individuals in each population used the optimal decision bound. Third, in contrast, there were clear differences between the PD patients and normal controls in the selective attention condition, in which the irrelevant dimension was present in the stimulus display. Whereas only 5 of 34 normal control data sets suggested deficits in selective attention, 12 of 34 PD data sets suggested deficits in selective attention. In other words, for a significantly larger proportion of the PD patients (PD: 35.29% vs. normal control: 14.70%), the irrelevant dimension interfered dramatically with the ability to attend selectively to the relevant dimension. Even so, the model-based analyses suggest nearly one third of the PD patients used the optimal, experimenter-defined rule.

These results suggest that when only one stimulus dimension is present (i.e., in the baseline condition) or when both dimensions are present and the participant is required to integrate information, PD patients show no performance deficits as compared with normal controls. However, when both dimensions are present and selective attention is required, a significantly larger proportion of the PD patients, as compared with normal controls, show a selective attention deficit. However, the fact that nearly one third of the PD patients were able to attend selectively in an optimal fashion suggests that there are at least two subtypes of PD patients present in our sample: those that have deficits in selective attention and those that do not.

These results are consistent with the fact that PD can present with heterogeneous cognitive profiles. Several investigators have suggested that only a subgroup of PD patients exhibit dementia during the course of their disease (Pirozzolo et al., 1982; Rajput, Offord, Beard, & Kurland, 1984). Although the prevalence of dementia in PD is not completely known, estimates range from as little as 9% to as high as 93%. Despite the inconsistencies in the prevalence of dementia, not all PD patients become demented. This fact suggests that PD can affect cognitive abilities in very different ways. In addition, those PD patients that do demonstrate cognitive deficits often display a heterogeneous profile of impairment. For example, Mortimer et al. (1987) administered a neuropsychological battery to a fairly large group of PD patients. These investigators identified three subtypes of PD patients: those with
memory and visuospatial impairments, those with a selective impairment in memory, and those with no cognitive deficits. Given these findings, it is not completely surprising that a subgroup of PD patients in our study performed optimally in terms of their selective attention abilities, whereas other PD patients demonstrated a significant deficit in their ability to attend selectively to the relevant target dimension.

The notion that PD can present with a heterogeneous profile in terms of the presence or absence of dementia is certainly not a new one (see Dubois et al., 1991; Mayeux & Stern, 1983). However, the present study goes beyond previous reports by indicating that even PD patients who are fairly homogeneous in terms of their level of dementia and their predominant symptom (i.e., 70% of the PD sample had tremor as their predominant symptom) can exhibit important subgroup differences. That is, even though our sample of patients as a whole had no dementia, we were still able to identify deficits in a subgroup of patients on a test of attention. Moreover, this significant subdivision of the PD patients occurred only within a specific aspect of attention: selective attention. These results suggest that important subdivisions within PD can be identified at a more precise level of cognitive functioning and that researchers do not have to rely on global measures of cognition for the identification of subgroups. The next logical step in this area of research is to identify which other aspects of cognition could also be used to delineate the most reliable and clinically meaningful subgroups of PD patients. It may be that performance on attentional functions is only one possible way in which to divide PD patients.

To further examine the possible implications of our model-based approach, we conducted subgroup analyses in which we compared PD patients that showed a selective attention impairment (PD-D subgroup) with those who did not (PD-ND subgroup). These analyses indicated that the two groups did not differ in terms of their total score on the DRS. This was not surprising given that this group of PD patients as a whole had no dementia. What was surprising and of interest was the finding that the two subgroups differed on the Conceptualization subscale of the DRS but not on any other subscales. This subscale assesses abstract reasoning and such measures are thought to be sensitive to the integrity of the frontal lobes (Lezak, 1995). Thus, it may be that those PD patients who demonstrated a selective attention deficit also had greater frontal lobe dysfunction. However, this possibility is highly tentative given the fact that the two subgroups did not differ on other DRS subscales thought to be sensitive to frontal lobe functioning, such as the Initiation and Perseveration subscale. Unfortunately, we did not administer more sensitive clinical measures of cognitive abilities during the same testing session, and therefore we are not certain that such subgroup differences would hold up under a more stringent test of these possible subgroup differences. Research is currently underway in our laboratories that we hope will replicate and extend the present findings. Specifically, we hope to identify subgroups of PD patients (using model-based analyses) and then compare these subgroups on more sensitive clinical neuropsychological measures.

The results of the present study are consistent with other studies that have identified an impairment in patients with PD on more traditional tasks of visual perception (Boller et al., 1984; Hovestadt et al., 1987; Levin, 1990; Levin et al., 1990; Raskin et al., 1990). However, the present study indicates that such deficits may not simply be due to an impairment in perceptual processes per se. As we pointed out earlier, participants were presented with similar stimuli (i.e., a horizontal and a vertical line) in both the dimensional integration and selective attention conditions, thus assuring that the perceptual input for the two conditions was analogous. The only difference in these two conditions was the rule participants had to apply in order to categorize the stimuli correctly. These two rules placed greater demands on different aspects of attention. The fact that PD patients were impaired only in the selective attention condition, and not in the dimensional integration condition, suggests that the different attentional demands of the task, and not a deficit in the perceptual processing of the visual stimuli, caused the impairment. Thus, it may be that PD patients will demonstrate impairment on visual-perceptual tasks in which they have to attend selectively to a target in the presence of irrelevant visual information, but they may not be as impaired under other conditions.

The finding that PD patients are impaired in selective attention processes is consistent with the previous findings. PD patients show impairments on tests requiring them to identify visual targets among distracter items (Pillon et al., 1989), attend to auditory targets in one ear and ignore distracting stimulation in the other ear (Sharpe, 1992); attend to letter sequences presented at one spatial location while distracting visual information is presented at another location (Sharpe, 1990), and identifying stimulus colors while presented with conflicting semantic information (i.e., the Stroop task; Henik, Singh, Beckley, & Rafaal, 1994; Hietanen & Teravainen, 1986). The identification of attention deficits in PD patients have led several investigators to argue that deficits of PD patients in other aspects of cognition may also be mediated by an attentional impairment (Brown & Marsden, 1990; Karayannis, 1989). For example, researchers have suggested that an attentional impairment may underlie deficient performance of PD patients on tests of concept formation (Caltagirone, Carlesimo, Nocentini, & Vicari, 1989), memory (Sharpe, 1992), set shifting (Downes, Sharp, Costall, Sagor, & Howe, 1993; Owen et al., 1993; Richards, Cote, & Stern, 1993), visual search (Villardita, Smiri, & Zappala, 1983), dual task abilities (Horstink, Berger, van Paedoneck, van den Bercken, & Cools, 1990), language comprehension (Grossman, Crino, Reivich, Stern, & Hurtig, 1992; Grossman et al., 1993), and motor programming (Jones et al., 1994). These studies provide support for the hypothesis that an attentional impairment may be associated with impaired performances of PD patients on visual-perceptual tests. Although attentional impairment may be an important factor in deficits of PD patients on traditional tasks of visual perception, other investigators have provided data suggesting that deficits of PD patients may be mediated by dysfunction in other cognitive areas. For example, Bondi et al. (1993) found that compared with normal subjects, PD patients without dementia were impaired on traditional measures of visual-perceptual and constructional abilities relative to normal controls. However, when these investigators covaried out
participants' performances on tests believed to be sensitive to executive functions, the group differences on the visual-perceptual and constructional tasks did not emerge. Similarly, Grossman et al. (1993) also found a significant relationship between performances of PD patients on a constructional task and tests of executive functioning. These studies suggest that executive functions may also mediate PD patients' performances on tasks of visual-perception.

An important question arises regarding the specific cognitive mechanisms underlying poor performances in PD patients in the selective attention condition. That is, PD patients may be impaired in attending selectively on this task for several different reasons. For example, the PD patients may be impaired in inhibiting the processing of the irrelevant component of the visual stimuli, thereby enabling the irrelevant component to interfere with the perception of the relevant component. This could lead to the selective attention deficit exhibited by the PD patients. Alternatively, the PD patients may have been able to inhibit the processing of the irrelevant component but were impaired in maintaining the selectivity of their attention to the relevant visual component. Although it is not possible to rule out either explanation based on the results from this study, the finding of previous reports support the latter explanation. Specifically, Wright et al. (1990) found that PD patients demonstrate an abnormally rapid disengagement of attention from the location at which a visual cue last appeared. Thus, these patients were impaired in maintaining attention to a cued spatial location. Filoteo et al. (1994, 1995) found that PD patients demonstrated a deficit in maintaining attention to different levels of hierarchical stimuli and that those patients who demonstrated a greater deficit in maintaining attention also committed more perceptual errors in identifying the visual targets. Other investigators have also reported deficits in maintaining attention in patients with PD (Downes et al., 1989). Such a deficit in maintaining attention could account for the pattern of impairments in this study. Specifically, it could be that in the selective attention condition, which required participants to make perceptual decisions about single stimulus features in the presence of an irrelevant feature, attention of PD patients rapidly disengaged from the target feature. That is, the PD patients may have been unable to maintain the selectivity of their attention on the relevant feature and their attention shifted to the irrelevant component, thereby allowing the irrelevant feature to interfere with their perception of the relevant component. Although this is one possible explanation, other possibilities, such as a deficit in inhibitory processes, will have to be investigated before any conclusions can be drawn about the specific cognitive mechanisms involved in selective attention deficits of PD patients.

There are several areas of neuropathology that may be associated with PD selective attention deficits of PD patients in this study. Given that the primary focus of neuropathology in PD is in the substantia nigra of the basal ganglia (Agid, 1991; Albin et al., 1989; Gibb, 1991), it might be concluded that the selective attention deficits exhibited by these patients are a result of damage to these brain regions. Indeed, other reports indicate that the basal ganglia may be involved in selective attention processes. Photon emission tomography has identified hypermetabolism within the basal ganglia in normal humans during the administration of selective attention tasks (Corbetta et al., 1991), and several animal studies implicate the basal ganglia in various attention processes (see Hassler, 1978; Robbins, & Brown, 1990; Rolls et al., 1984). Therefore, it is possible that these structures are directly involved in performing certain neurocognitive processes that are necessary for selective attention, and dysfunction of these structures (such as that seen in PD) will result in selective attention deficits.

Although the basal ganglia is a good candidate for the neuropathological locus of deficits of PD patients in attending selectively, there are other neuroanatomical regions that may also play a role in their deficits. The basal ganglia is highly connected to other brain regions, and it may be that damage within the basal ganglia results in dysfunction in these other structures (Alexander, DeLong, & Strick, 1986; Cummings, 1993). In other words, the selective attention deficits exhibited by PD patients in this study may not be due to damage within the basal ganglia per se but rather is the result of dysfunction in other brain regions secondary to basal ganglia damage. For example, it is possible that dysfunction in the prefrontal cortex results in PD patients selective attention deficits. Patients with frontal lobe pathology are impaired on selective attention tasks (see Foster, Eskes, & Stuss, 1994; Knight, 1991), and PD patients can demonstrate hypometabolism in frontal structures (Wolfson, Leenders, Brown, & Jones, 1985). In support of this frontal explanation, Grossman and colleagues (1992, 1993) found that hypometabolism in the medial aspects of the frontal lobes (as measured by PET) was associated with impaired performances of PD patients on an attention demanding sentence processing task. Similarly, using event-related potentials, Stam et al. (1993) found that disturbed processing negativity (an event-related potential associated with selective attention) was associated with impaired performance on tests believed to be sensitive to frontal dysfunction. Thus, it may be that a disconnection between the basal ganglia and the frontal lobes results in frontal deficits, and it is this frontal dysfunction that accounts for selective attention deficits of PD patients.

It is also possible that the loss of inhibitory input into the superior colliculus via dysfunction of the frontal lobe structures or the basal ganglia may have resulted in impairment of PD patients in this study. The superior colliculus receives input from the frontal eye field via the caudate nucleus and the pars reticulata of the substantia nigra (Goldberg, Eggers, & Gouras, 1991). One of the main functions of the superior colliculus is to trigger reflexive saccades (Rafal, Smith, Krantz, Cohen, & Brennan, 1990; Wurtz & Munoz, 1995), and it appears that the frontal-striatal circuit may be involved in inhibiting this process (Guitton et al., 1985; Henik et al., 1994). Dysfunction within the frontal lobes or the basal ganglia could then result in disinhibition of the superior colliculus, which in turn could result in an increased propensity to orient gaze to stimuli that are not currently fixation. This deficit in maintaining fixation could then possibly manifest as a deficit in selective attention.

Although each of these neuropathological correlates of selective attention deficit of PD patients is possible, it is also possible that their impairment on such tasks is a result of dysfunction of a more widespread distributed neuroanatomical network (Goldman-Rakic, 1988; Mesulam, 1990; Posner & Petersen, 1990), possibly involving frontal regions, the basal
ganglia, the superior colliculus, and thalamic structures. However, each of these regions likely contribute a unique operation in selective attention processes, and future research should focus on delineating the nature of these unique contributions. Such research would lead to a better understanding of the neurocognitive mechanisms underlying attentional impairments of PD patients. We feel that quantitative model-based approaches can significantly improve our chances of delineating the independent and interdependent contributions of these important brain regions.

References


### Appendix

**Model Fitting and Testing**

When testing the validity of a model with respect to a particular data set, one must determine (a) how the unknown parameters will be estimated, and (b) how well the model describes or “fits” the data. In addition, because many of the models under consideration are special cases of a more general model (e.g., the optimal model is a special case of the suboptimal dimensional integration model, where the decision bound slope and intercept are fixed at the optimal values), and a more general model, by definition, will provide a better absolute account of the data, it would be advantageous to have some method for determining whether the improvement in fit for the general model is statistically significant.

The method of maximum likelihood provides a powerful tool for dealing with each of these issues (Ashby, 1992b; Wickens, 1982). Consider an experiment with Categories A and B and a set of n stimuli S1, S2, …, Sn. For each stimulus, a particular model predicts the probabilities that the participant will respond A and B, which is denoted by P(A|Si) and P(B|Si), respectively. The results of an experimental session are a set of n responses, r1, r2, …, rn, where we arbitrarily set r1 = 1, if a Category A response was made to Stimulus i, and r1 = 0, if a Category B response was made. According to the model and with responses that are independent, the likelihood of observing this set of n responses is

\[ L(r_1, r_2, \ldots, r_n) = \prod P(A|S_i)^{r_i} P(B|S_i)^{1-r_i}. \]

The maximum likelihood estimators are those values of the unknown parameters that maximize L(r1, r2, …, rn), denoted L(α) for short. Thus the goal of maximum likelihood is to adjust the parameters of the model until L(α) is maximized.

Maximum likelihood estimates also provide a rigorous method for testing whether a general model provides a more accurate description of a set of data than a restricted model. In the selective attention condition here, the suboptimal dimensional integration model is the most general model because both the slope and intercept are estimated from the data. The suboptimal selective attention model is less general because only the intercept is estimated from the data, whereas the slope is fixed at zero. The optimal selective attention model is the least general model because both the slope and intercept are fixed a priori. Although the suboptimal dimensional integration model (the most general model) is guaranteed to have the largest estimated likelihood, L(r), a likelihood ratio test can be used to determine whether the improvement in fit for the suboptimal dimensional integration model is statistically significant.

If we want to determine whether the suboptimal dimensional integration model provides a significant improvement in fit over the suboptimal selective attention model, a likelihood ratio test would proceed as follows. First, one estimates the parameters from both the suboptimal dimensional integration and suboptimal selective attention models with maximum likelihood techniques. Second, one forms the ratio of the estimated likelihood values for each model. Specifically, one computes the ratio \( \lambda = L_1/L_2 \), where \( L_1 \) is the likelihood value for the suboptimal selective attention model (the less general model) and \( L_2 \) is the likelihood value for the suboptimal dimensional integration model (the more general model). The more general model provides no improvement in fit over the less general model when \( \lambda = 1 \). The general model provides an improvement in fit when \( \lambda < 1 \). Third, one computes \( \chi^2 = -2 \ln(L_1) - 2(\ln L_1 - \ln L_2) = 2(\ln L_2 - \ln L_1) \), where \( \ln \) is the natural logarithm. Most parameter estimation routines attempt to minimize some loss function; thus when fitting the models, we usually attempt to minimize the negative of the natural log of the likelihood ratio, -\( \ln L(r) \), which is mathematically equivalent to maximizing L(r). Assuming the null hypothesis that the suboptimal selective attention model (i.e., the less general model) is correct, chi-square has an asymptotic chi-square distribution with degrees of freedom equal to the difference in the number of free parameters. In our example, the suboptimal dimensional integration model has one additional free parameter, so the degrees of freedom equal 1. Finally, the observed value of chi-square can be compared with the appropriate critical value. If the observed value exceeds the critical value, then one concludes that the additional parameters of the suboptimal dimensional integration model (i.e., the more general model) provided a significant improvement in fit (see Wickens, 1982, for an overview of parameter estimation and hypothesis testing using the method of maximum likelihood).

In this article, we were interested in determining the decision bound...
model that we refer to as the best fitting (also called the most parsimonious) model. This is the model with the fewest number of free parameters that was not significantly improved on the basis of likelihood ratio tests (see Wickens, 1982) by a more general model.

Figure 4 depicts data from a participant in the selective attention condition who exhibited a deficit in selective attention. This determination was made after conducting a series of likelihood ratio tests. These tests are summarized below. First, the optimal, suboptimal selective attention, and suboptimal dimensional integration models were applied to the data. The $-\ln(L(r))$ for the three models (in the same order) were 10.78, 10.76, and 5.48. Second, a likelihood ratio test was conducted between the optimal and suboptimal selective attention models. This computation yielded $\chi^2(1, N = 120) = 0.04$. The critical value for $\alpha = 0.05$ for a chi-square distribution with 1 degree of freedom $= 3.84$. Because the observed value did not exceed the critical value, the optimal model was not rejected in favor of the suboptimal selective attention model. Third, a likelihood ratio test was conducted between the optimal and the suboptimal dimensional integration model. This computation yielded $\chi^2(2, N = 120) = 10.60$. In this case, there are 2 degrees of freedom, and the critical value ($\alpha = 0.05$) is 5.99. Because the observed value did exceed the critical value, we reject the optimal model in favor of the suboptimal dimensional integration model. Fourth, a similar comparison is made between the suboptimal selective attention model and the suboptimal dimensional integration model. Again the observed value exceeded the critical value, and the suboptimal selective attention model was rejected in favor of the suboptimal dimensional integration model. In this instance, the most parsimonious model is the suboptimal dimensional integration model. Finally, because the suboptimal dimensional integration model was favored, the inference is drawn that the participant showed a deficit in selective attention.

Figure 5 depicts data from a participant in the selective attention condition who exhibited no deficit in selective attention but utilized a selective attention rule that was suboptimal. This determination was made after conducting a similar series of likelihood ratio tests. As before, the optimal, suboptimal selective attention, and suboptimal dimensional integration models were applied to the data. The $-\ln(L(r))$ for the three models (in the same order) were 14.35, 7.23, and 7.21. A likelihood ratio test was conducted between the optimal and suboptimal selective attention models yielding $\chi^2(1, N = 120) = 14.24$ and leading us to reject the optimal model in favor of the suboptimal selective attention model. Then a likelihood ratio test was conducted between the suboptimal selective attention model and the suboptimal dimensional integration model. This computation yielded $\chi^2(1, N = 120) = 0.04$ and led us to reject the suboptimal selective attention model. Finally, because the suboptimal selective attention model was favored, the inference was drawn that the participant did attend selectively but used a suboptimal selective attention criterion.

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