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Piéron's Law Holds During Stroop Conflict: Insights Into the Architecture of Decision Making

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Abstract

Piéron's Law describes the relationship between stimulus intensity and reaction time. Previously (Stafford & Gurney, 2004), we have shown that Piéron's Law is a necessary consequence of rise-to-threshold decision making and thus will arise from optimal simple decision-making algorithms (e.g., Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006). Here, we manipulate the color saturation of a Stroop stimulus. Our results show that Piéron's Law holds for color intensity and color-naming reaction time, extending the domain of this law, in line with our suggestion of the generality of the processes that can give rise to Piéron's Law. In addition, we find that Stroop condition does not interact with the effect of color saturation; Stroop interference and facilitation remain constant at all levels of color saturation. An analysis demonstrates that this result cannot be accounted for by single-stage decision-making algorithms which combine all the evidence pertaining to a decision into a common metric. This shows that human decision making is not information-optimal and suggests that the generalization of current models of simple perceptual decision making to more complex decisions is not straightforward.

Keywords: Decision making; Stroop task; Piéron's Law; Response conflict; Color saturation

1. Introduction

1.1. Stroop processing

The Stroop task (Stroop, 1935) is a paradigmatic selection task in which a failure of attentional control leads to response conflict (MacLeod & MacDonald, 2000). Participants are presented with a colored word stimulus and must respond to the stimulus color. The word

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can be neutral with respect to the color (e.g., the word ''HORSE'' in red ink) or itself be the name of a color. Thus, the response activated by this cognitive element of the stimulus (the meaning of the word) can be conflicting (e.g., the word ''GREEN'' in red ink) or congruent (e.g., the word ''RED'' in red ink) with the response activated by the merely perceptual element of the stimulus (the physical color). In the conflict condition, selection involves the resolution of a contradiction between one response based on the color aspect of the stimulus and a different response based on the word aspect of the stimulus. The resolution of this conflict causes delays in responding and errors—the *interference* typically seen in the conflict condition of the Stroop task. Traditionally, interest in the Stroop task has focused on the demonstration it provides of the power of overlearned behaviors (in this case, word-reading) to interfere with response selection. Here, we are more concerned with the use of the Stroop task as a thoroughly investigated example of decision making under conditions of stimulus conflict, in which elements of different kinds (words and physical colors) are involved in affecting the response.

1.2. Piéron's Law

Piéron (1952) demonstrated that the physical intensity of a stimulus is systematically related to the simple reaction time (RT), so that the average RT is given by

$$\mathrm{RT} = R_0 + kI^{-\beta}, \tag{1}$$

where R_0 is the asymptotic RT, a fixed component of response which cannot be reduced, I is the physical intensity of the stimulus, and k and β are constants. This relation is known as *Piéron's Law*. Piéron's Law has been shown to hold for simple RTs across different sensory modalities (Luce, 1986). It holds for luminance of white light, for amplitude of pure tones, and even for taste with respect to the concentration of a substance diluted in water (Bonnet, Zamora, Buratti, & Guirao, 1999). Pins and Bonnet (1996) have demonstrated that Piéron's Law can hold in choice RTs. Their experiments showed that the exponents of the Piéron's Law function that fit the stimulus intensity to RT data are consistently similar within a particular modality whatever the task complexity is. From this they infer the following: first, luminance processing continues to some critical level which remains constant; secondly, the duration of post-luminance processing must have also been constant; and finally, the two components of processing combine additively. This inference from additive factors to separate processing stages is common in the analysis of RT data, and something which we discuss further next.

1.3. Modeling decision making

The RT that we record in response to a stimulus is the result of a psychological decision process. Indeed, all behaviors, however simple, must be the result of a decision process. Looking at decision making and building mathematical models which account for choice RTs and error rates has a long history within psychology (Luce, 1986). Recently, progress on the neural basis of decision making has been made by combining electrophysiological recording of single-neuron activity with choice models from mathematical psychology. RTs from human and non-human primates gathered from simple, two-choice, perceptual decisions can be used to parameterize decision models. Analogs of components of these models can be found in neural activity (Ratcliff, Cherian, & Segraves, 2003; Reddi, Asrress, & Carpenter, 2003). Obviously, such an impressive confluence of psychological theory, behavior, and neural measurement raises hope of further rapid progress on understanding the neural basis of decision making in general, beyond the simple perceptual decision making of the paradigms currently used (Gold & Shadlen, 2001; Opris & Bruce, 2005; Platt, 2002). The diffusion model (Ratcliff, 1978; Ratcliff & McKoon, 2008) is perhaps the preeminent example of a model from this mathematical psychology tradition. Ratcliff has suggested that, for two-alternative forced choice tasks, the diffusion model is the only account which can explain the distribution of RTs for correct responses, as well as the speed and distribution of incorrect responses, under different urgency-accuracy conditions (Ratcliff & Rouder, 1998). More recently, the optimality of the diffusion model for making urgency-accuracy trade-offs in two-choice situations under conditions of uncertainty has been demonstrated (Bogacz et al., 2006). A notable feature of the diffusion model, in common with many mathematical models of decision making, is that it combines the *evidence* favoring the possible choices into a single term—termed ''the drift'' in the diffusion model framework. There are obvious benefits of combining evidence into a common metric which determines what response is made and after how long. As well as bringing analytic tractability to the model, it should be apparent that optimal decision making requires the trade-off of different factors influencing the decision. A common metric facilitates an optimal trade-off in the same way that a common currency facilitates economic communication. Gold and Shadlen (2002) outline the theoretical underpinnings of such a ''weight of evidence'' metric and discuss its neural instantiation.

1.4. Piéron's Law and decision making

Stafford and Gurney (2004) showed that Piéron's Law arises naturally from a number of models of response selection. The geometry of the choice process, which is obeyed by simple decision models, such as the diffusion model (Ratcliff, 1978; Ratcliff & McKoon, 2008), the LATER model (Carpenter, 1981, 2004), and simple single-neuron decision models (see Dayan & Abbott, 2001), produces a rise-to-threshold time which is determined by the height of the threshold and the rate of signal rise. Thus, if stimulus intensity, I, is proportional to the evidence in favor of selection, D, and RT is characterized by a rise-to-threshold process, then

$$\mathrm{RT} \approx R_0 + kD^{-\beta}, \tag{2}$$

where k and β are constants which depend on the critical threshold and the particular properties of the stimulus and R_0 is the fixed component of decision time. D is equivalent to the momentary weight of evidence; this is the drift rate in the diffusion model and equivalent to the input in a simple neuron model. Stafford and Gurney (2004) go on to show that Piéron's Law-like functionality will result from any choice process that relies on the linear rise of a signal to threshold. This kind of process is represented graphically in Fig. 1.

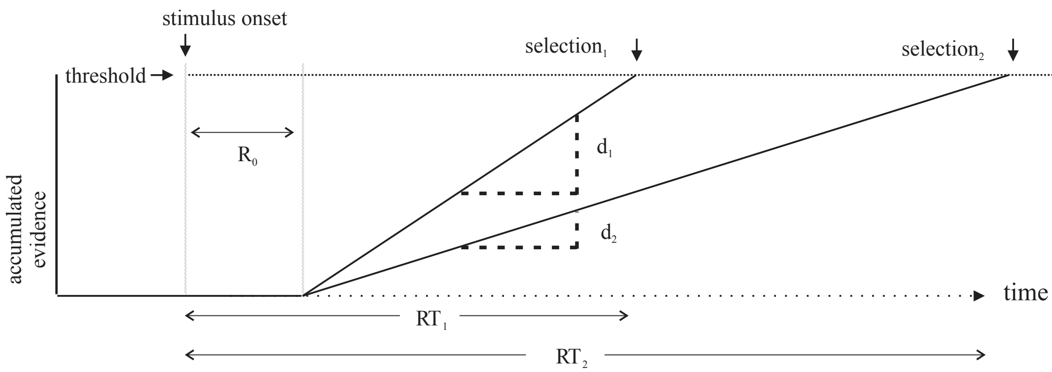

Fig. 1. Geometry of selection by linear rise to threshold. Drift rates d_1 and d_2 produce selection times RT_1 and RT_2, respectively.

In important related work, Palmer, Huk, and Shadlen (2005) show that a model of decision making based on the diffusion model gives a unified account of how both response time and response accuracy vary with stimulus strength.

1.5. The current investigation

These results show both empirically (Pins & Bonnet, 1996) and theoretically (Stafford & Gurney, 2004) that we would expect that perceptual detection can be an important determinant of choice response times and will follow a Piéron's Law-like regularity. However, because Stafford and Gurney (2004) demonstrate that a Piéron's Law-like relation is a necessary consequence of any rise-to-threshold selection process, it is not clear whether perceptual detection and subsequent decision are integrated within a single stage, as Ratcliff (2001) implies, and as theoretical analyses demand for their definition of optimality to be satisfied (Bogacz et al., 2006; Gold & Shadlen, 2002), or whether perceptual detection is a separate stage which is purely additive to subsequent decision processing as implied by Pins and Bonnet (1996) and explicitly claimed by Carpenter (2004). This is the context for the present investigation, which involves investigating how choice RTs are affected when both perceptual and cognitive elements of a task are manipulated simultaneously.

1.6. Analysis of selection controlled by a common metric

The current experiment involves manipulating the cognitive and perceptual elements in a standard Stroop task. The Stroop condition—either control, conflict, or congruent—determines the putative *cognitive* element of the task. This is the factor which influences whether the response decision based on the color of the stimulus is slowed (interference) or speeded (facilitation). The *perceptual* element is manipulated by changing the percentage color saturation of the stimulus while keeping the absolute level of light constant. The relationship between simple RT and color saturation has not, to our knowledge, been directly tested before. It is strongly predicted that this relation will follow Piéron's Law in the Stroop control condition, where no word is presented. The question of interest is whether color saturation and Stroop condition will interact. If the perceptual and cognitive elements of the task are represented independently in separate detection and decision stages, then RTs in the three Stroop conditions should be separated by a constant amount across different saturation levels—in other words, Piéron's Law should hold for each condition, and the functions that fit the data in each condition should have similar exponents. In the terms of the additive factors method (AFM; Sternberg, 1998), the two factors would be additive. If, on the other hand, the representation of the perceptual and cognitive elements of the task are combined within a single metric at a single common stage of decision making—such as the diffusion model—then the difference between the Stroop conditions will vary according to saturation level. In this case, although RTs might follow Piéron's Law within conditions, the functions would have different exponents between conditions. There would be an interaction of factors. To see why this is required by a ''single metric'' simple decision model, we will consider how the decision would be computed by the diffusion model, the preeminent, and demonstrably optimal, model of simple decision making (Ratcliff, 1978; Ratcliff & McKoon, 2008). Within the terms of the diffusion model, we can assume that the drift rate will be larger if color saturation is higher. If the congruency condition affects the total drift rate by a constant amount, then we can predict that, if the perceptual and cognitive evidence is combined into a single common metric, the difference between RTs in the control and conflict conditions will differ at different saturation levels; and, for similar reasons, between these conditions and the congruent condition. To see why this is, simply note that the core relationship between RT and drift is given by Eq. 2. As RT is a non-linear function of *D*, decreases in *D* will have larger effects if *D* is smaller. If drift is increased due to higher color saturation, the RT difference between the control and conflict conditions will decrease, despite the constant change in evidence contributed by the cognitive aspect of the stimulus. Therefore, the size of the interference effect—the difference in RT between the control and conflict conditions—will be larger if total drift is smaller, for example, when color saturation is less. Geometrically, this is shown in Fig. 2. In other words, this analysis predicts that if the color saturation and word condition of the stimulus contribute directly and independently

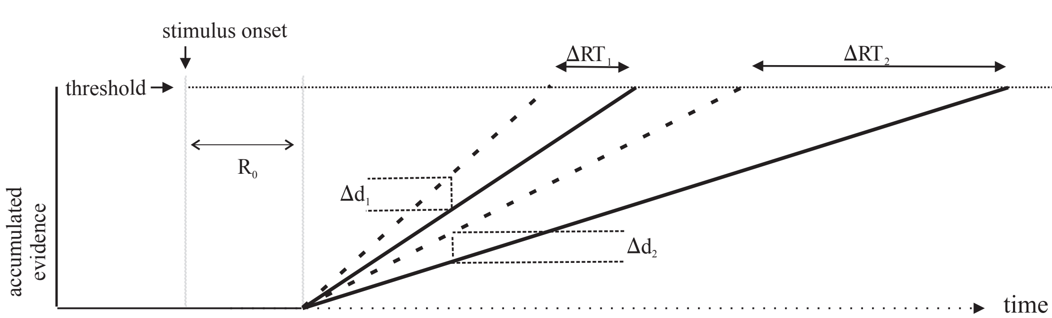

Fig. 2. Although the increases in drift rate Δd_1 and Δd_2 are of the same magnitude ($\Delta d_1 = \Delta d_2$), they result in different increases in reaction time, so that $\Delta RT_1 < \Delta RT_2$.

to the strength of evidence for a decision, and if these evidence values, although independent, are combined into a common metric, then the two factors will have an interactive effect on RTs. (Note that this is the same mechanism that produces the shape of the slope of Piéron's Law—increases in stimulus intensity produce diminishing decreases in RT.)

2. Experiment 1

Our analysis shows clearly that a simple decision algorithm that combined evidence from perceptual and cognitive elements of the stimuli into a common metric will produce an interaction of the intensity and Stroop condition factors. To test this, we conducted the standard Stroop color-naming task, using stimuli which varied in color saturation.

2.1. Methods

2.1.1. Participants

Twenty University of Sheffield undergraduate students (15 female, average age = 20.05, *SD* = 3.85) participated in exchange for partial fulfillment of a course requirement.

2.1.2. The task

As per the conventional single-trial Stroop task, participants were instructed to name the ink color, not the word, of a colored word stimulus.

2.1.3. Materials

The stimulus were created using Corel Graphics Suite (version 11.0, Corel Corporation, Ottawa, Canada), in 24 pt AventGarde Bk BT typeface. There were three colors of stimuli—red, yellow, and blue—and three conditions; either the word was congruent with the color, conflicted with the color, or was neutral with respect to the color (this condition used the letters ''XXXX'' instead of color word). Each color of stimuli, in each condition, was presented at five different levels of color saturation: 55%, 45%, 32%, 22%, and 15%. Hue was kept constant within each color-set, and brightness was constant across all stimuli.

2.1.4. Design

There were two factors, Stroop condition (control, conflict and congruent) and stimuli intensity (at five levels of saturation). After nine practice trials with the lowest saturation stimuli, the participants completed four blocks of trials in which they saw all 60 possible stimuli in a random order. The total of 240 trials was divided into two halves by a rest break.

2.1.5. Stimuli and responses

All testing was conducted under constant levels of illumination. Stimuli were presented on a black background on a PC running Windows 98 using E-Prime (version 1.1) and a ADI GD910T monitor. Subjects were positioned 45 cm from the monitor, upon which stimuli subtended at a visual angle of up to 19°. Trials began with the presentation of a fixation point, which was replaced by the appearance of the stimulus after 1,000 ms. The stimuli remained for up to 3,000 ms or until a response was registered, whichever was shorter. The interval between stimulus onset and the onset of the participant's vocal response was recorded by a microphone triggering the voice key of a PST Serial Response Box (SRBox).

2.2. Results

Incorrect responses, those faster than 300 ms (deemed to be due to an irrelevant sound triggering the voice key) and those slower than 1,500 ms were removed from the analysis. These invalid trials were only 6% of the total. The mean RTs for the color-naming experiment are shown in Fig. 3. A two-factor within-subjects ANOVA was performed. There was a clear effect of condition, $F(2,18) = 106.97$, $p < .0001$. As expected, the conflict condition was slower than the control condition and the congruent condition was fastest of all. The effect of stimulus intensity was also highly significant, $F(4,16) = 19.16$, $p < .0001$; higher color saturations were associated with faster RTs in all three Stroop conditions. There was, however, no interaction of color saturation and Stoop condition, $F(8,12) = 0.433$, *ns*—as can be seen from the graph (Fig. 3), the difference between the conditions remains constant at all levels of stimulus intensity. Bonferroni post hoc tests showed that both the control–conflict and control–congruent condition means were significantly different ($p < .01$ for both).

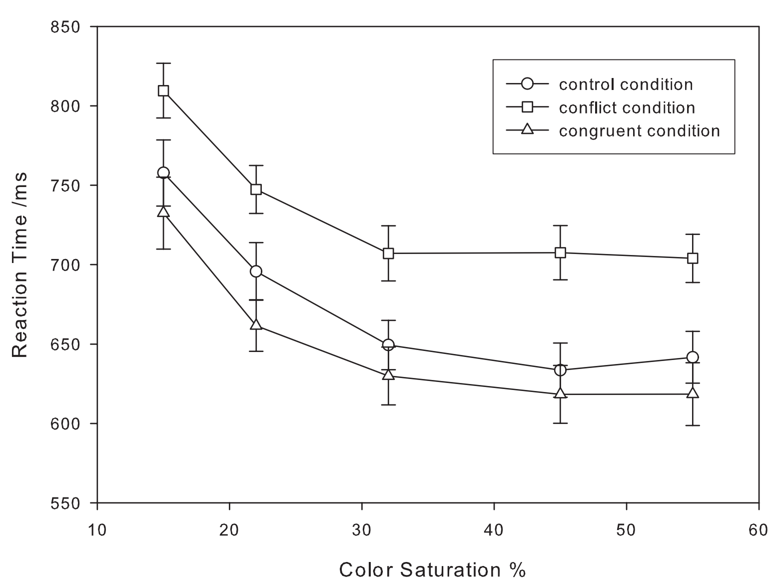

Fig. 3. Mean reaction times for different stimulus color saturations in all three Stroop conditions. Standard error bars shown ($n = 20$).

2.2.1. Fitting data with Piéron's Law

Following the procedure described in Stafford and Gurney (2004), we can fit Piéron's Law curves to the color saturation—RT curves in all three Stroop conditions. Table 1 shows the Pearson's r correlation coefficients between the empirical data and Piéron's Law curves of best fit, as well as the asymptotes and exponents. Inspection of the exponents of the functions fitted to the data averaged across individuals shows them to be very similar. It is also possible to fit Piéron's Law functions to individuals' data in each of the three conditions. An ANOVA on the β values of these fitted functions shows that there is no significant difference between the conditions, $F(2,38) = 2.151$, $p = .130$. The mean correlations between the individually fitted Piéron's Law functions and the observed data for each condition are shown in Table 2. An within-factor ANOVA demonstrated that there was no significant difference between these correlations across conditions, $F(2,18) = 0.086$, $p = .918$.

2.3. Discussion of Experiment 1

The color-naming experiment demonstrates that a color saturation to RT Piéron's Law holds in all three basic Stroop conditions. As far as we are aware this is the first demonstration that Piéron's Law holds for color saturation. It is also a confirmation of the finding of Pins and Bonnet (1996) that Piéron's Law holds for choice RTs as well as simple RTs, but using a different task. It is the first demonstration of Piéron's Law in a Stroop task, and in so much is the first demonstration in a response conflict situation where the choice is based on a single stimulus. The lack of interaction between Stroop condition and color saturation appears to suggest that perceptual salience and cognitive salience are not combined into a single ''response salience'' value. Additionally, we can note that these data suggest that perceptual detection is a significant factor compared to decision, even in a cognitive task such

Table 1
Fit data for Piéron's Law against the color saturation—reaction time functions in all three Stroop conditions, Experiment 1

Stroop Condition	Correlation Coefficient	R_0	β
Control	0.992*	621	1.83
Conflict	0.994*	697	2.37
Congruent	0.999*	611	2.34

Note. *Significant $p < .0001$.

Table 2
Correlations between observed data and predictions from fitting Piéron's Law for each individual in each condition, Experiment 1

	Correlation Coefficients	
Stroop Condition	*M*	*SD*
Control	0.844	0.237
Conflict	0.830	0.152
Congruent	0.809	0.276

as the Stroop task. The correlations between Piéron's Law functions and the within-condition data for each individual are high, although interestingly not as high as when Piéron's Law functions are fitted to the means across individuals. There is no significant difference between the fits for different conditions, reinforcing the conclusion that Piéron's Law holds equally for the different conditions, and the shape of the function does not interact with Stroop condition.

3. Experiment 2: Separated Stroop

It is possible that the additivity of Experiment 1 is due to the integration of the word and color stimuli; note that in the conventional Stroop task, the word is formed from the color patch that varies in saturation. A version of the Stroop task, the ''separated Stroop,'' exists whereby the word and color stimuli are not integrated but are presented adjacent to each other. A diminished but reliable Stroop effect persists in these conditions (MacLeod, 1998). We conducted a second experiment, identical in method to Experiment 1 bar that the word and the color were presented separately immediately above and below fixation (randomly alternating). The results are shown in Fig. 4. A two-factor within-subjects ANOVA was performed. The results were very similar to those for Experiment 1. There was a clear effect of condition, $F(2,26) = 91.126$, $p < .0001$. The effect of stimulus intensity was also highly significant, $F(4,24) = 78.594$, $p < .0001$. There was no interaction of color saturation and Stoop condition, $F(8,20) = 1.840$, *ns*. The difference between the conditions appeared to remain constant at all levels of stimulus intensity. Bonferroni post hoc tests showed that

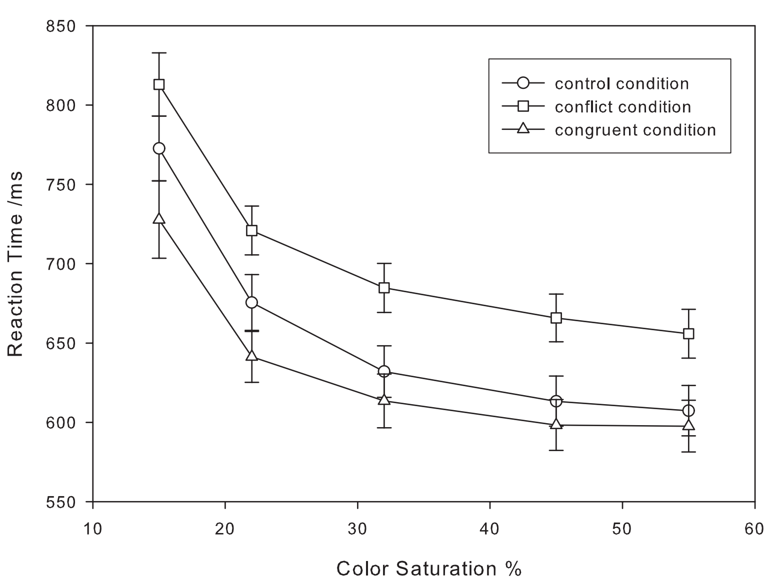

Fig. 4. Separated Stroop task. Mean reaction times for different stimulus color saturations in all three Stroop conditions. Standard error bars shown ($n = 28$).

Table 3
Fit data for Piéron's Law against the color saturation—reaction time functions in all three Stroop conditions, Experiment 2

Stroop Condition	Correlation Coefficient	R_0	β
Control	1.000*	595	2.07
Conflict	0.999*	646	2.02
Congruent	0.999*	593	2.61

Note. *Significant $p < .0001$.

Table 4
Correlations between observed data and predictions from fitting Piéron's Law for each individual in each condition, Experiment 2

	Correlation Coefficients	
Stroop Condition	*M*	*SD*
Control	0.936	0.102
Conflict	0.948	0.067
Congruent	0.914	0.133

both the control–conflict and control–congruent condition means were significantly different ($p < .001$ for both). These data are well fitted by Piéron's Law functions, as shown in Table 3. An ANOVA on the exponents of the Piéron's Law functions fitted to the individual data shows that there is no significant difference between the exponents for each condition, $F(2,54) = 1.628$, $p = .206$. The mean correlations between the individually fitted Piéron's Law functions and the observed data for each condition are shown in Table 4. An within-factor ANOVA demonstrated that there was no significant difference between these correlations across conditions, $F(2,25) = 0.670$, $p = .521$.

3.1. Discussion of Experiment 2

As with Experiment 1, the perceptual factor (color saturation) and cognitive factor (Stroop condition) did not interact, instead combining additively. This suggests that the results of Experiment 1 were not due to a peculiarity of the integrated stimulus presentation but are instead fundamental to the processing demanded by the Stroop task. Similarly to the results from Experiment 1, the correlations between Piéron's Law function and the data for each individual are lower than the correlations for the mean data. Both sets of correlations for Experiment 2 are better than the corresponding correlations representing the fit of Piéron's Law functions in Experiment 1. Although this could be due to the separation of the Stroop and color information in the stimuli that was the motivation for Experiment 2, it could also be due to the greater number of participants and hence data points in Experiment 2. The difference between the goodness-of-fit for the mean and individually fitted functions suggests that Piéron's Law shows through more clearly when results are averaged over trials and individuals. Whether this is due to the inherent noisiness of the processes involved (certainly true to some extent), or additionally because the underlying function within individuals or even within individual decisions is other than a Piéron's Law power function is beyond the scope of this article to address. For example, it is known that average of exponential functions can produce power functions. For an introduction to the statistical complexities of fitting power functions to data, see Clauset, Shalizi, and Newman (2009). For our purposes, the important point is that for both Experiments 1 and 2, the data are well fitted by Piéron's Law, for both mean results and for the results of individuals. Furthermore, there is no suggestion that the application of Piéron's Law is restricted to data from any particular Stroop condition. For both the mean data and individual's data, the exponents of the fitted Piéron's Law functions are not significantly different across Stroop conditions, supporting our inference that Piéron's Law does not interact with Stroop condition.

4. General discussion

These data show that Piéron's Law holds for color saturation and under conditions of active response conflict, whereby two responses are both triggered by the same stimulus. These are both novel results. The latter demonstrates an extension of the relevance of this function beyond mere perceptual tasks and into the realm of cognitive tasks involving complex stimulus–response translation and active response conflict. The consistency of the results across the conventional and separated Stroop suggest that it is not due to some quirk of color information and word information being physically co-incident, as in the conventional Stroop, but is rather due to the nature of processing required by the task. The pattern of RTs in these experiments gives us some insight into the architecture of decision making. The additivity of the Stroop condition and color intensity factors, at first glance, seems to support the view that simple decision making *can* consist of two stages, detection and decision. This would certainly be the interpretation according to the AFM and is consonant with our analysis of the diffusion model style response mechanism. This analysis shows that a single-stage response mechanism which linearly combines stimulus evidence into a common metric cannot account for the pattern of data in tasks like this. This is important because the optimal integration of information over time and from different sources requires a common metric to represent the combined weight of evidence (Gold & Shadlen, 2002). Proofs of the optimality of diffusion model type evidence integrators (Bogacz et al., 2006) mean that alternative methods which are not formally equivalent must be non-optimal (according to this information integration definition of optimality). In the context of the current investigation, consider the scenario in which processing supporting responding to a stimulus was split into a detection stage, which recognized the elements of the stimulus display, and a decision stage, which reconciled these elements to calculate a response. In principle, this would mean that total decision time to barely detectable stimuli could be unfeasibly long (theoretically infinite, if it were not for noise in the decision process), even if the detection of such stimuli would require a response of the utmost urgency. In the current task, such a division would produce the lack of interaction between stimulus intensity and Stroop condition that we see here. This result is, of course, not proof that we cannot combine information from across stimulus dimensions to make a response. Rather, it is just a demonstration of a specific exception to the predicted RT performance from a naive informationally optimal model of evidence accumulation. Thus, this result fits within a wider body of work that shows that human decision making is not optimal (Kahneman, Slovic, & Tversky, 1982), when optimal is defined with respect to rational information integration. Previously, we have shown that models of optimal decision making may lead to ''maladaptive'' behavior when integrated into models of simple choice tasks (Stafford & Gurney, 2007). In particular, information optimality implemented by accumulation of evidence toward a threshold can lead to unrealistically long-selection times (if positive and negative evidence for a selection is closely matched), or selection of behaviors for which evidence is non-zero but negligible (if evidence accumulation is allowed to precede for a long enough time). Obviously, both of these outcomes would be undesirable for a real-world agent that must make rapid decisions, even between closely matched alternatives, and requires some minimal threshold of evidence for selection of behaviors. Here, we show that even simple choice tasks, such as the Stroop, can be made to reveal non-optimality in human decision making. A host of results show that the human and non-human primate brain can integrate information optimally, and in ways that can be modeled by simple choice models (Gold & Shadlen, 2007; Ratcliff et al., 2003). We suggest that although the primate brain can do this, it is not a complete explanation of primate choice behavior and its neural instantiation. If we expand our purview to include even marginally non-simple perceptual decisions, then the decision-making architecture reveals systematic non-optimalities. Our suspicion is that, as with many cognitive biases, the source of these non-optimalities will be the requirements of evolutionary adaptiveness (Gigerenzer & Todd, 1999). See Redgrave, Prescott, and Gurney (1999) for a discussion of this point specifically in the context of selection. These results also have an obvious interpretation according to the logic of the AFM (Donders, 1868–1869/1969; Sternberg, 1998). Although this approach is not currently fashionable, many authors do still infer multiple loci from the appearance of additive factors such as we found in our experiments (Pins & Bonnet, 1996; Woodman, Kang, Thompson, & Schall, 2008). Recent theoretical results have made it clear that the inference from additive factors to discrete processing stages is not trivial (Thomas, 2006; Townsend & Wenger, 2004), and our own work on processing stages in this version of the Stroop task confirms this (T. Stafford & K. Gurney, forthcoming). Whether or not it is possible to infer separate stages from additive factors, it is clear that, in our color saturation varying Stroop task at least, the underlying architecture for decision making appears to be able to resolve perceptual and response conflict in a way that keeps their effects on decision times separate. The implication of this is that although great progress has been made in modeling simple perceptual decisions, and although pervasive regularities, such as Piéron's Law, may hold in more complex decisions, the generalization of these models to marginally more complex decisions is likely to be far from straightforward.

Acknowledgments

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