Bayesian multi-level modelling for predicting single and double feature visual search

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# Abstract

Performance in visual search tasks is frequently summarised by “search slopes”

- the additional cost in reaction time for each additional distractor. While search tasks with a shallow search slopes are termed efficient (pop-out, parallel, feature), there is no clear dichotomy between efficient and inefficient (serial, conjunction) search. Indeed, a range of search slopes are observed in empirical data. The Tar- get Contrast Signal (TCS) Theory is a rare example of quantitative model that attempts to predict search slopes for efficient visual search. One study using the TCS framework has shown that the search slope in a double-feature search (where the target differs in both colour and shape from the distractors) can be es- timated from the slopes of the associated single-feature searches. This estimation is done using a contrast combination model, and a collinear contrast integration model was shown to outperform other options. In our work, we extend TCS to a Bayesian multi-level framework. We investigate modelling using normal and shifted-lognormal distributions, and show that the latter allows for a better fit to previously published data. We run a new fully within-subjects experiment to at- tempt to replicate the key original findings, and show that overall, TCS does a good job of predicting the data. However, we do not replicate the finding that the collinear combination model outperforms the other contrast combination models, instead finding that it may be difficult to conclusively distinguish between them.

*Keywords:* Visual search, Efficient search, Parallel processing

# 1 1. Introduction

2 Visual search, where participants are asked to find a target within a cluttered

3 scene, has been extensively studied within psychology. Several models have been

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4 developed that can generate testable predictions about how different types of dis-

5 tractors and targets affect search efficiency. One of the key distinctions in the field

6 has been between efficient (also referred to as parallel or pop-out) and inefficient

7 (serial) search. These are often studied in the context of the regression slope be-

8 tween the number of distractors and mean reaction time, which has been termed

9 the *search slope*. When the search slope is shallow (usually positive, but occasion-

10 ally negative e.g. [(Rangelov et al.,](#_bookmark75) [2017)),](#_bookmark75) the search is called efficient or parallel,

11 and the addition of more non-target distractors has little impact on an observers

12 difficulty in finding a target. When the slope is steeper, each additional distrac-

13 tor has a noticeable impact on increasing difficulty, and the search is described

14 as inefficient or serial. However, the distinction between these types of search is

15 often less clear in real experimental data, with a range of different search slopes

16 being seen for different types of targets and distractors [(Duncan and Humphreys,](#_bookmark36)

17 [1989;](#_bookmark36) [Cave and Wolfe,](#_bookmark32) [1990;](#_bookmark32) [Wolfe,](#_bookmark84) [1998;](#_bookmark84) [Liesefeld et al.,](#_bookmark54) [2016).](#_bookmark54) Recent work

18 has also attempted to model the variation in search slopes at the boundary between

19 inefficient and efficient search [(Liesefeld et al.,](#_bookmark54) [2016).](#_bookmark54)

20 In the current study, we are interested in what has traditionally been termed

21 efficient or parallel search, and the factors that affect search slope in these condi-

22 tions. Recent work has suggested that for efficient search, there is a logarithmic

23 relationship between distractor set size and reaction time, and that this relation-

24 ship can be modified by target-distractor similarity [(Buetti et al.,](#_bookmark29) [2016),](#_bookmark29) providing

25 evidence that search behaviour in parallel search is more complex than has pre-

26 viously been assumed. This observation has formed the basis of the ‘Target Con-

27 trast Signal (TCS) Theory’ [(Lleras et al.,](#_bookmark56) [2020),](#_bookmark56) which aims to provide a means

28 of predicting observer search slopes for new search arrays by quantifying target-

29 distractor differences. For example, by measuring search slopes for conditions in

30 which the distractors differ from the target along a *single feature* (e.g. colour *or*

31 shape), it has been shown that you can predict search times for arrays in which

32 the target differs from the distractors along two features (e.g., colour *and* shape)

33 which we refer to here as *double feature* search [(Buetti et al.,](#_bookmark30) [2019)](#_bookmark30) (but simi-

34 lar paradigms have been known by other names e.g. ’redundant feature search’

35 [(Krummenacher and Mu¨ller,](#_bookmark51) [2012;](#_bookmark51) [Mordkoff and Yantis,](#_bookmark63) [1991)).](#_bookmark63) Here, we aim

36 to replicate and extend this work both theoretically and empirically, to test the

37 generalisability of the TCS model, and to suggest ways in which the TCS model

38 could be modified to generate better predictions.

39 *1.1. Previous Work*

40 Many different forms of visual search models have been proposed. One well

41 developed class of models are the saliency models, which aim to predict eye move-

42 ments during scene viewing, including visual search. They rest on the assump-

43 tion that fixations are directed to objects or locations that are most dissimilar to

44 the background or other objects in the visual display [(Itti and Koch,](#_bookmark44) [2000;](#_bookmark44) [Itti](#_bookmark45)

45 [et al.,](#_bookmark45) [1998;](#_bookmark45) [Koch and Ullman,](#_bookmark47) [1987).](#_bookmark47) While the original saliency model was

46 able to predict fixation allocation in a visual search task above chance (P[arkhurst](#_bookmark72)

47 [et al.,](#_bookmark72) [2002),](#_bookmark72) further research demonstrated that a comparable level of performance

48 could be achieved using a simple central fixation bias heuristic (T[atler,](#_bookmark77) [2007).](#_bookmark77) The

49 saliency models have since been extended and improved (see for example [Zhang](#_bookmark93)

50 [et al.](#_bookmark93) [(2008)):](#_bookmark93) however, the main issue with this family of models remains their

51 limited usability in complex real-life search arrays (T[atler et al](#_bookmark78)., [2011;](#_bookmark78) [Koehler](#_bookmark48)

52 [et al.,](#_bookmark48) [2014),](#_bookmark48) and even in abstract laboratory search arrays [(Kotseruba et al.,](#_bookmark49) [2020).](#_bookmark49)

53 In addition, in most instances of visual search, the target is clearly defined (i.e. the

54 goal is to find a specific object) and inspecting the most salient areas of the dis-

55 play may in these cases be inefficient. Finally, by focusing on eye movements,

56 these models do not necessarily provide a theoretical framework for the cognitive

57 processes underlying visual search.

58 Perhaps the most established class of models of visual search are based around

59 Feature Integration Theory (T[reisman and Gelade,](#_bookmark80) [1980),](#_bookmark80) which has been modi-

60 fied and extended by Wolfe and colleagues in the Guided Search Model [(Wolfe](#_bookmark88)

61 [et al.,](#_bookmark88) [1989;](#_bookmark88) [Wolfe,](#_bookmark85) [2014).](#_bookmark85) These theories have been developed using data from

62 visual search tasks with discrete sets of abstract items. These models combine

63 top-down influences (how closely an item resembles the observer’s goal) with

64 bottom-up image properties. For example, if one’s goal (top-down processing)

65 is to find a red horizontal bar, all the red and horizontal items in a visual search

66 display will be given greater weight than distractors (e.g. vertical and blue items)

67 in the model. The salience of a given object in the display (how distinctive it is

68 from the surrounding objects) also activates bottom-up processing. For instance, a

69 blue item among red items is ranked higher than red among orange items. In such

70 cases, a salient item can capture attention even without resembling the target.

71 Combining bottom-up and top-down sources of activation generates an activation

72 map which generates a prediction of the order in which stimuli are processed in

73 visual search. Other extensions to these models have been proposed, such as the

74 Dimension Weighting Account, in which saliency weightings are assigned to dif-

75 ferent target ’dimensions’ (e.g. colour or shape), helping to explain results where

76 varying the target dimension within blocks of trials leads to longer reaction times

77 than where the dimension remains consistent within a block [(Krummenacher and](#_bookmark51)

78 [Mu¨ller,](#_bookmark51) [2012).](#_bookmark51) Thus, these models aim to produce a representation of the visual

79 properties of the distractors at each location in the visual field. However, these

80 are predominantly qualitative models, and thus it is difficult to use them to make

81 specific quantitative predictions.

82 TCS falls under a class of models that take a different approach, in that they

83 focus solely on representing the difference between targets and distractors. For

84 example, in work on eye movement patterns, it has been proposed that perfor-

85 mance in inefficient (serial) visual search is mostly determined by the size of the

86 ‘functional viewing field’, whose size varies as a function of target-distractor sim-

87 ilarity [(Hulleman and Olivers,](#_bookmark41) [2017).](#_bookmark41) Similarly, work on attention has proposed

88 the notion of ‘relative features’, where attention is tuned to feature relationships

89 i.e. the appearance of the target relative to distractors in the environment [(Becker](#_bookmark27)

90 [et al.,](#_bookmark27) [2014;](#_bookmark27) [Becker,](#_bookmark26) [2010).](#_bookmark26) TCS also has features in common with other models

91 that propose parallel identification of all items in a scene, with diffusion based

92 mechanisms for identifying targets from distractors [(Moran et al.,](#_bookmark60) [2013,](#_bookmark60) [2016).](#_bookmark61)

93 However, TCS [(Lleras et al.,](#_bookmark56) [2020)](#_bookmark56) aims to provide a unifying framework that can

94 make quantitative behavioural predictions for visual search based on this general

95 assumption. As such, it is an attractive candidate model for a formal registered

96 replication.

97 A key assumption of the TCS model is that behaviour is determined by com-

98 paring the target template (held in memory) with every element present in the

99 scene in parallel. This allows the visual system to reject peripheral non-targets

100 quickly; the speed at which items are evaluated is determined by how different the

101 item is from the template through an evidence accumulation process (formally,

102 the slope of the logarithmic function is assumed to be inversely proportional to the

103 overall magnitude of the contrast signal between the target and distractor). The

104 model thus focuses on an initial, efficient processing stage of search; if sufficient

105 evidence is not accumulated during this process, the model posits that a second

106 stage is entered, requiring a sequence of eye movements to search for the target

107 in a serial manner. TCS has been successful in predicting a number of empirical

108 results, including search performance in heterogeneous scenes based on parame-

109 ters estimated in homogeneous scenes, both with artificial stimuli [(Buetti et al.,](#_bookmark29)

110 [2016;](#_bookmark29) [Lleras et al.,](#_bookmark55) [2019)](#_bookmark55) and with real-world objects visualised on a computer

111 display [(Wang et al.,](#_bookmark82) [2017).](#_bookmark82) Table [1](#_bookmark1) provides an overview of studies investigating

112 the TCS framework to date.

113 The original version of the TCS model is essentially a (natural) log-linear

114 model in the number of distractors. The full model contains a variable *L*, which

115 represents the number of different types of distractors present in the display. How-

116 ever, in our paper, we will follow [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) and only consider the specific

117 case of *L* = 1, of a target among a homogeneous set of distractors. In this case,

118 the TCS model can be represented in the following way:

*R*ˆ*T* = *a* + *D* log(*NT* + 1) (1)

119 The intercept, *a*, corresponds to search arrays in which only the target is

120 present and there are no distractors. *NT* is the total number of distractors.

121 *1.2. Rationale for proposed work*

122 While many aspects of the TCS framework have been tested, with extremely

123 promising results, there remains a great deal of scope for verification of some of

124 the key findings to date, and extensions of aspects of the model. In all implementa-

125 tions of TCS so far, predictions of search efficiency (e.g. in heterogeneous scenes)

126 have been made on the average of a group of participants, using data from a dif-

127 ferent group performing a different task (e.g. searching in homogeneous scenes).

128 Thus, we know that TCS can replicate group-level averages between subjects in

129 search well, but we do not know to what extent it is also able to make predictions

130 at the individual level. This is particularly important given that conclusions based

131 on aggregate data can be different from those that take individual differences into

132 account; in one study where participants searched for a target in an array of ran-

133 domly oriented line segments, aggregating the data suggested that participants

134 were using a stochastic search model [(Nowakowska et al.,](#_bookmark68) [2017).](#_bookmark68) However, when

135 considering each participant individually, it became clear that there was a high

136 level of heterogeneity in responses, with some participants performing close to

137 optimally, and others actually performing worse than chance [(Nowakowska et al.,](#_bookmark68)

138 [2017).](#_bookmark68) Similarly striking variability has also been reported in other search studies

139 [(Irons and Leber,](#_bookmark42) [2016,](#_bookmark42) [2018;](#_bookmark43) [Clarke et al.,](#_bookmark33) [2022a).](#_bookmark33)

140 Taking search time distributions into account is also important for constrain-

141 ing theories of visual search [(Wolfe et al.,](#_bookmark89) [2010;](#_bookmark89) [Liesefeld and Mu¨ller,](#_bookmark53) [2020):](#_bookmark53) for

142 example, they have been used to help distinguish between models that make sim-

143 ilar predictions at the level of average reaction times [(Moran et al.,](#_bookmark61) [2016,](#_bookmark61) [2017).](#_bookmark62)

144 Including subject and trial level data into our implementation of the TCS will

145 therefore further aid model development and assumption testing.

146 We also extend the TCS model into a Bayesian framework, where we begin

147 with existing ’prior’ beliefs that are updated with data to give ’posterior’ beliefs

148 that can be used for inference [(McElreath,](#_bookmark59) [2020).](#_bookmark59) We think this has a number

Reference Overview

[Buetti et al.](#_bookmark29) [(2016)](#_bookmark29) For efficient search with a specific target, there is a log-

arithmic relationship between distractor set size and re- action time. The steepness of this relationship is modu- lated by distractor-target similarity, with steeper slopes for more similar distractors.

[Wang et al.](#_bookmark82) [(2017)](#_bookmark82) Data from homogeneous search arrays can be used to

predict search reaction times in heterogeneous displays containing images of real-world objects, using an equa- tion assuming parallel, unlimited capacity, exhaustive processing, and independence of inter-item processing.

[Madison et al.](#_bookmark57) [(2018)](#_bookmark57) Logarithmic efficiency in efficient search cannot be ex-

plained by crowding in peripheral vision.

[Ng et al.](#_bookmark67) [(2018)](#_bookmark67) Logarithmic efficiency in efficient search cannot be ex-

plained by eye movements.

[Lleras et al.](#_bookmark55) [(2019)](#_bookmark55) Validation of previous results showing data from homo-

geneous search arrays can be used to predict reaction times in heterogeneous displays. Distractor-distractor interactions can also facilitate processing when nearby items are similar to each other.

[**Buetti et al.**](#_bookmark30)[**(2019)**](#_bookmark30)Data from search arrays where the distractors are dis-

tinguished from the target by one feature can be used to predict search reaction times in displays with com- pound stimuli, defined by two features. Reaction times can be predicted using a collinear contrast integration model, which assumes that the overall target-distractor contrast is the sum of the contrasts from the two feature vectors separately.

[Lleras et al.](#_bookmark56) [(2020)](#_bookmark56) Full proposal of the Target Contrast Signal Theory,

proposing that the initial stage of processing computes a difference signal between each item in the scene and the target template, using this to determine which items in the scene are unlikely to be the target.

[Ng et al.](#_bookmark66) [(2020)](#_bookmark66) Attention works in a two stage process, first discard-

ing target-dissimilar distractors in a distributed, parallel way. Focused spatial attention then visits target-similar items at random.

[Xu et al.](#_bookmark90) [(2021)](#_bookmark90) Extension of [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) to new features (shape

and texture), which combine according to a Euclidean metric (orthogo6nal contrast integration model).

Table 1: An overview of work on the Target Contrast Signal Theory. The key paper for our replication is highlighted.

149 of advantages over frequentist approaches. Perhaps most importantly, Bayesian

150 models are highly flexible. We demonstrate how we are able to specify a model

151 that is able to more accurately represent the distribution of responses (for exam-

152 ple, by specifying a response distribution that avoids predicting negative reaction

153 times) with a relatively complex model structure, that can be fit to a relatively

154 small amount of pilot data: something that would be challenging within a fre-

155 quentist framework. We also believe that Bayesian models offer very intuitive

156 methods for model testing and comparison and straightforward interpretation of

157 results, and we hope that this manuscript can act as a demonstration of these ben-

158 efits, showing how they can be applied to real scientific questions beyond the

159 simplified examples often found in textbooks or tutorials.

160 In the current manuscript, we focus on replicating and extending findings from

161 [Buetti et al.](#_bookmark30) [(2019).](#_bookmark30) In their study, participants searched for a target in a scene of

162 homogeneous distractors (see Figure [1).](#_bookmark2) First, parallel search efficiency (mea-

163 sured by the logarithmic search slope) was estimated for cases where the distrac-

164 tors varied from the target in one dimension: either colour (e.g. a cyan target being

165 searched for in either yellow, blue or orange distractors) or shape (e.g. a semicir-

166 cle target in either circle, diamond or triangle distractors). New participants then

167 searched for the same targets in displays where the distractors were compounds,

168 differing from the target in both colour and shape (e.g. searching for a cyan semi-

169 circle in either blue circles, orange diamonds or yellow triangles). The logarithmic

170 search slopes in the initial experiments were then used to predict the logarithmic

171 slopes and reaction times using a number of models. The authors found that the

172 best model was a ‘collinear contrast integration model’ where the distinctiveness

173 scores were summed along each attribute in the unidimensional experiments, cre-

174 ating an overall contrast score that was used for compound stimuli predictions.

175 In our registered replication, we will attempt to verify the conclusions of [Buetti](#_bookmark30)

176 [et al.](#_bookmark30) [(2019),](#_bookmark30) that the collinear contrast integration model does indeed offer the

177 best characterisation of contrast signal combinations in visual search within the

178 TCS framework.

179 We begin by verifying the analysis of [Buetti et al.](#_bookmark30) [(2019).](#_bookmark30) We then describe

180 our proposed replication study, showing with pilot data how we are able to extend

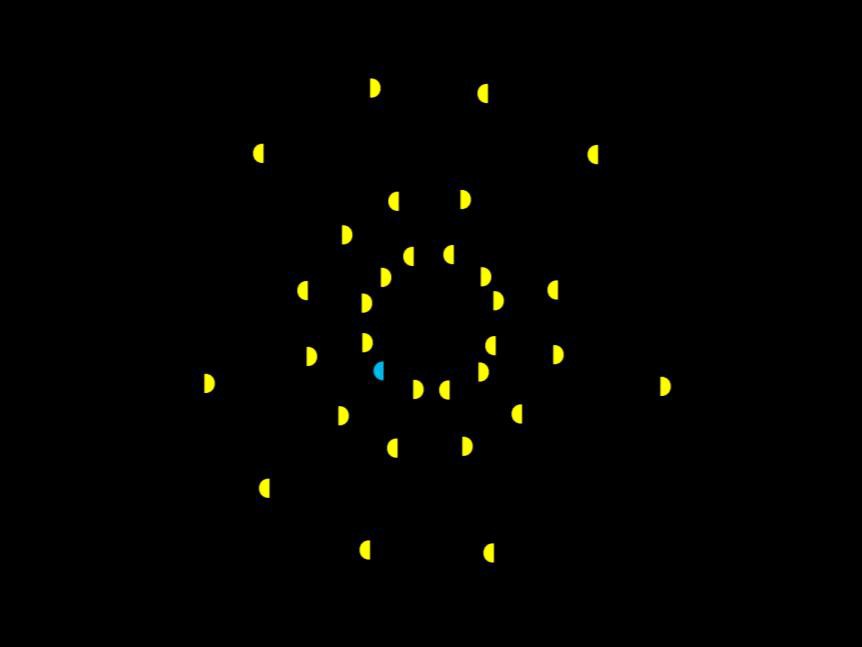
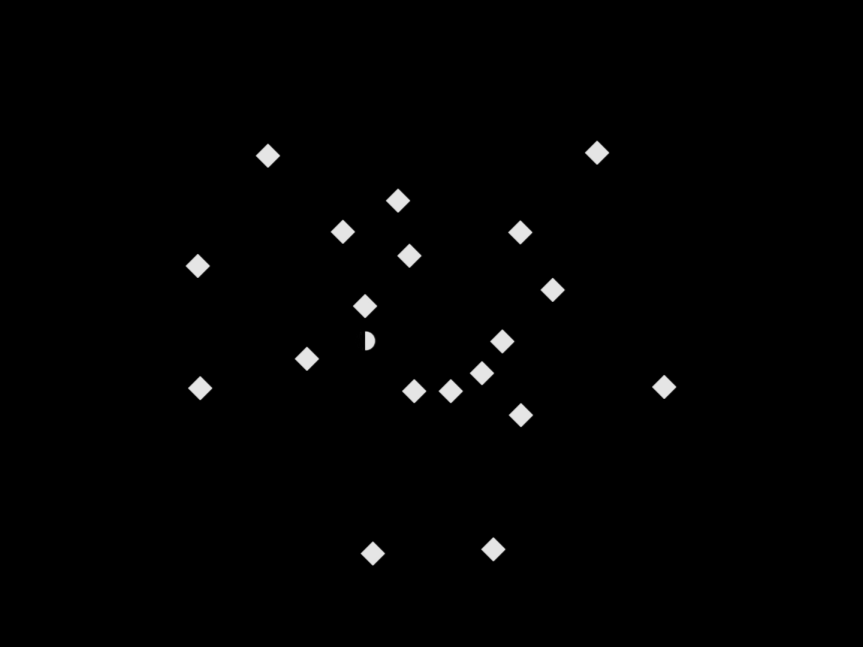
181 their model of how multi-dimensional contrasts are calculated, both by incorpo-

182 rating a multi-level design to predict within-subjects effects and by utilising a

183 Bayesian generalised linear model framework to better represent the distribution

184 of responses (e.g. avoiding predicting negative reaction times, accounting for un-

185 certainty in model predictions).

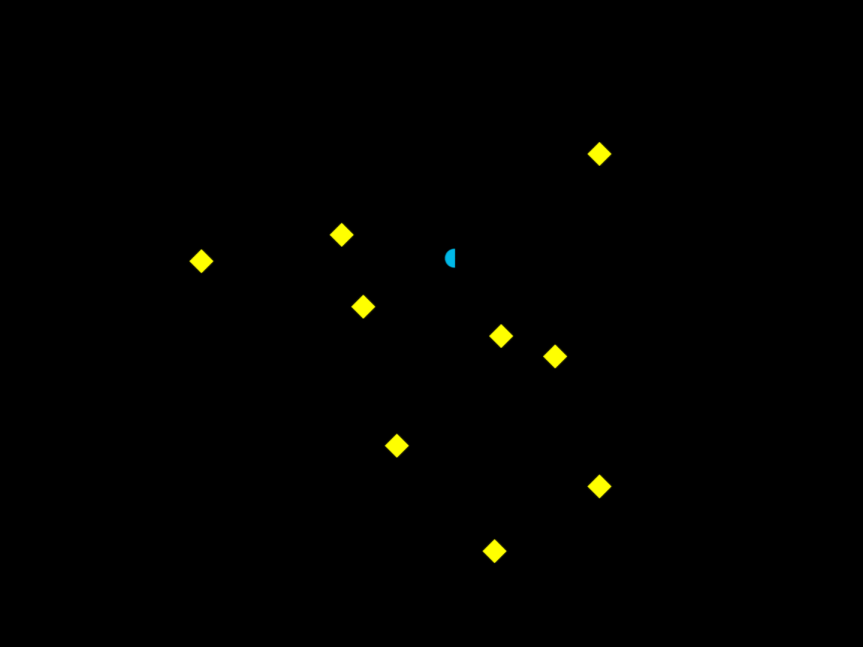
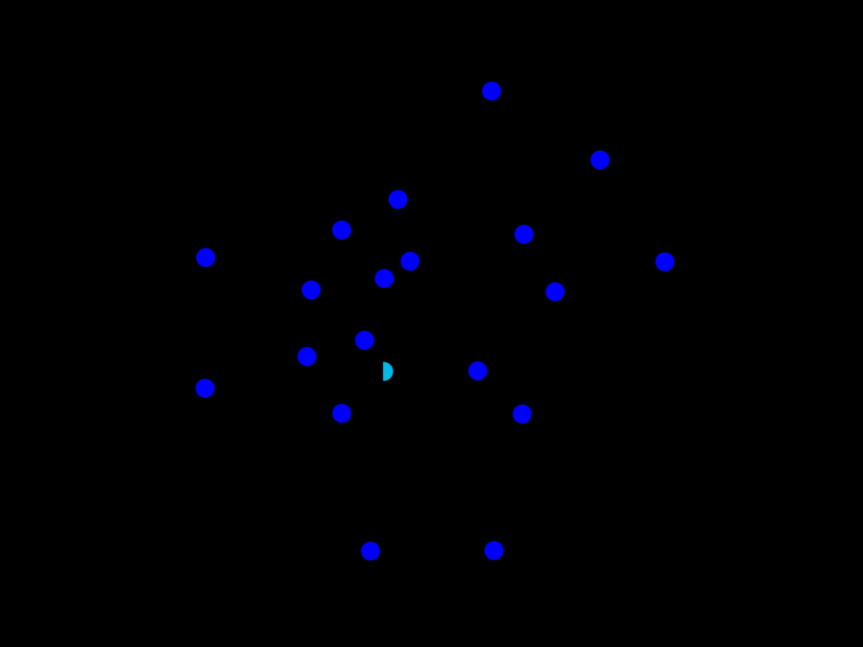
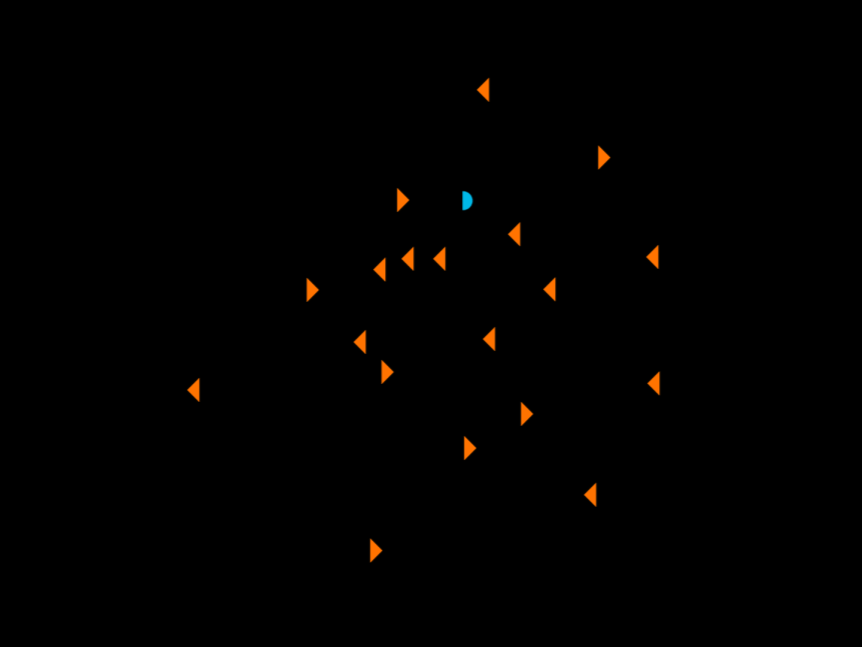


Figure 1: Example stimuli from [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) Top left: Expt 1A. Here, the target is a blue semicircle within a set of homogeneous (yellow semicircle) distractors. Top right: Expt 1B. The target is a grey semicircle in circular grey distractors. Bottom left: Expt 2A. The target is a blue semicircle in orange diamond distractors. Bottom middle: Expt 2B. The target is a blue semicircle in dark blue triangle distractors. Bottom right: Expt 2C. The target is a blue semicircle in yellow circular distractors.

# 186 2. The Target Contrast Model

187 We first describe the original Target Contrast Model, as presented in [Buetti](#_bookmark30)

188 [et al.](#_bookmark30) [(2019)](#_bookmark30) and verify that we can succesfully replicate the original analysis

189 (both using frequentist modelling and Bayesian modelling; see *Supplementary*

190 *Materials - Computational Verification)*.

191 *2.1. TCS modelling overview*

192 In Experiment 1a of [Buetti et al.](#_bookmark30) [(2019),](#_bookmark30) participants searched for a cyan

193 semicircle target among blue, yellow or orange semicircular distractors i.e. they

194 searched for a target that differed from the distractors by a *single feature* (colour).

195 The experiment was then repeated (1b) using a different single feature (shape,

196 with participants searching for the semicircular target within triangle, circle or di-

197 amond distractors). In Experiments 2a, 2b and 2c, participants again searched for

198 a cyan semicircle, but this time, the distractors differed in both shape and colour.

199 We will refer to these conditions as *double features*. Note, unlike in standard con-

200 junction searches, in this paradigm, the distractors are all identical with respect to

201 these features (i.e, orange triangles). Examples of all these stimuli are shown in

202 Figure [1.](#_bookmark2) [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) also carried out a replication of their basic results

203 using slightly different target and distractor stimuli (Experiments 3 and 4).

204 The *Target Signal Contrast* theory is built around a linear model for predicting

205 mean reaction times from the logarithm of the number of distractors (see Equation

206 [1).](#_bookmark0) In particular, the TCS theory allows us to predict the value of the logarithmic

207 slope, *D*c,s, in this condition based on the corresponding *Di* in the single feature

208 search experiments.

209 *2.1.1. Calculating the intercept, a, and the logarithmic slope parameter, Di*

210 Experiments 1a and 1b and 3a and 3b were used to calculate the logarithmic

211 slope parameter *Di*. In all experiments, the number of distractors varied, allowing

212 the data to be used to fit a log-linear model for reaction times, where reaction

213 times increase logarithmically with *NT* , the number of distractors (see Equation

214 [1).](#_bookmark0) In the original model the error distribution was assumed to be normal. Thus

215 the results of Experiments 1 and 3 were used to calculate *Di*, for each type of

216 distractor. When colour varied, we will refer to *Dc*, for *c* = 1*,* 2*,* 3. Similarly for

217 shape we will denote this (*Ds*), and the compound features are denoted as (*Dc,s*).

218 Fitting the model specified in Equation [1](#_bookmark0) to the data, we obtain the values for

219 *Dc* and *Ds* given in Table [2.](#_bookmark3) As can be seen, the more similar the distractors are to

220 the target, the steeper the slope parameter is.

|  |  |  |  |
| --- | --- | --- | --- |
| feature | *Dc* | feature | *Ds* |
| blue | 76.8 | triangle | 141.1 |
| yellow | 16.0 | diamond | 77.2 |
| orange | 9.8 | circle | 62.1 |

Table 2: A table of *Di* values for Experiment 1a and 1b. See *Supplementary Materials - Computa- tional Verification* for full values for all experiments.

221 *2.1.2. Estimating Dc,s, the logarithmic slope parameter for compound features*

222 In the context of the current experiments, the core idea of TCS theory is that

223 we can estimate the (natural) logarithmic slope parameter for a double feature

224 visual search from the slopes parameters in the two independent single feature

225 searches i.e., *Dc,s* = *f* (*Dc, Ds*). [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) tested three different models

226 for predicting *D* for compound colour-shape stimuli. The best feature guidance

227 model (Equation [2)](#_bookmark4) suggests that when the target and lures differ in two dimen-

228 sions, participants will choose to attend to whichever feature dimension is the

229 most discriminable (i.e. has the smallest *D* value):

*D*c,s = min(*D*c*, D*s) (2)

230 The orthogonal contrast combination model instead suggests that independent

231 feature dimensions comprise a multidimensional space, where an object can be

232 described by the overall vector in this space, and thus Dc*,*s can be represented as:

1

*D*c,s = j 1 2

( *D*c )

(3)

1 2

+ ( *D*s )

233 Finally, the collinear contrast integration model also assumes independence of

234 feature dimensions, but assumes that while the visual features create a multidi-

235 mensional space, the contrast between them is unidimensional. As *D* is assumed

236 to be inversely proportional to contrast, the equation can be written as follows:

1 1 1

237

*D*c,s = *D*c + *D*s (4)

[Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) found that with their dataset, the collinear contrast inte-

2

238

gration model was best able to predict *Dc,s* from *Dc* and *Ds*, with *R* = 0*.*915.

239

We verified we were able to replicate this result using the dataset available on

[1](#_bookmark7)

240

OSF (https://osf.io/f3m24/) and using the exclusion criteria originally applied;

241 see Figure [2](#_bookmark8) (left panel) and *Supplementary Materials - Computational Verifica-*

242 *tion* for details. We show that we are able to do this using both the frequentist

243 modelling approaches used in the original paper, and using Bayesian modelling.

244 *2.1.3. Estimating a, the intercept parameter for compound features*

245 As *a* is the intercept of the model, it represents how long observers take to find

246 a target when *NT* = 0, i.e., there are no distractors. As such, it should be inde-

247 pendent of both shape and colour, and can be thought of as the role of non-search

248 processes (such as motivation, motor preparation etc.) that influence reaction time.

249 In [Buetti et al.](#_bookmark30) [(2019),](#_bookmark30) *a* was calculated for each sub-experiment. Here, we follow

250 that method in order to replicate their results exactly.

1downloaded on 28th August 2020

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empirical D

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10 20 30 40 50

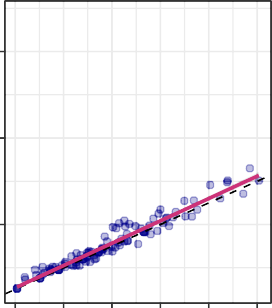
predicted D

1000

800

empirical mean rt (sec)

600



450 500 550 600 650 700

predicted rt (sec)

2500

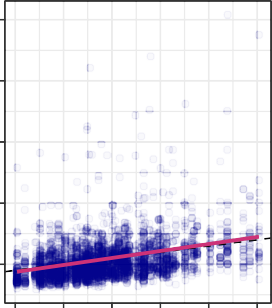
2000

sampled rt (sec)

1500

1000

500



450 500 550 600 650 700

predicted rt (sec)

Figure 2: (left) The collinear method for calculating *D* offers a good prediction. (centre) Using the TCS to predict reaction times. (right) Each dot now represents a randomly sampled reaction time from an observer. Note that there is greater spread in the data points here, due to the fact that there will be trial-to-trial variability due to target position, inter-item distances, observer differences and so on.

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* + 1. *Estimating mean reaction times*

Finally, we can use Equation [1](#_bookmark0) to predict mean reaction times. As can be seen in Figure [2](#_bookmark8) (centre panel), these predictions are essentially identical to the

2

254

255

empirical RT results: *R* = 0*.*93%.

* + 1. *Discussion*

256 While TCS theory offers a good prediction of search slopes and corresponding

257 mean reaction times for double feature search, there are two related limitations.

258 Firstly, it is unable to account for individual differences between observers, only

259 the changes to the sample average. Secondly, it cannot account for the distribution

260 of reaction times over multiple trials. Figure [2](#_bookmark8) (right panel) shows clearly that

261 these factors generate high levels of variability within the individual trial-level

262 data. To address these issues, we propose adapting TCS to make use of multi-

263 level modelling techniques. Multi-level models allow us to take into account the

264 hierarchical structure of the data (i.e. that each participant completes multiple

265 trials) in a way that does not require averaging, meaning that we are able to model

266 participant variability as well as group-level effects [(Gelman and Hill,](#_bookmark38) [2006).](#_bookmark38)

267 *2.2. A multi-level TCS*

268 Switching from a linear regression model to a multi-level model will allow

269 us to compute *D* for each participant, while simultaneously estimating the trial-

270 to-trial variance. We also switch from a frequentist to Bayesian framework, as

271 this allows us to naturally account for the uncertainty in the model’s predictions.

272 However, switching from linear regression to a multi-level model raises the prob-

273 lem of which distribution to use for modelling reaction times. Using a normal

274 distribution is unlikely to be satisfactory, as it is unable to account for the skew

275 frequently seen in reaction time distributions, and also allows the possibility of

276 negative reaction times. We can account for both of these problems by using a

277 log-normal distribution. We will also test whether a slightly more complex ex-

278 tension of this model, the shifted lognormal model (which allows the distribution

279 to be offset to the right i.e. mimicking the patterns seen in reaction time data,

280 where valid responses begin at around 100ms) offers any improvement in model

281 fit. Note that a Wald, or inverse Gaussian distribution, would also be a reasonable

282 distribution choice for this data given that TCS is based on a diffusion process e.g.

283 [(Moran et al.,](#_bookmark60) [2013),](#_bookmark60) and this distribution has been argued to be psychologically

284 more plausible (e.g. [Kieffaber et al.](#_bookmark46) [(2006),](#_bookmark46) though see [Matzke and Wagenmakers](#_bookmark58)

285 [(2009)):](#_bookmark58) we chose not to use this distribution as it often leads to computational is-

286 sues, which would make it harder for others to reproduce or build on our approach

287 later.

288 **3. Hypotheses**

289 We plan an experiment to test the extent to which the original results in [Buetti](#_bookmark30)

290 [et al.](#_bookmark30) [(2019)](#_bookmark30) replicate and generalise, using our new modelling approach.

291 *3.1. Proposed Modifications to Experimental Design*

292 In order to better test the above, and increase sensitivity, we propose to make

293 the following changes to the experiment described in [Buetti et al.](#_bookmark30) [(2019):](#_bookmark30)

294 1. **Within-subjects design.** This modification should give us greater power to

295 detect differences between different models, as well as allowing us to in-

296 vestigate how individual differences in the single-feature task might explain

297 differences in the double-feature task.

298

299 2. **Increase target-distractor similarity.** If the distractors are a very differ-

300 ent colour from the target, they may not distinguish well between different

301 contrast models. We will therefore run a version of the experiment where

302 the target is a red semicircle, with distractors being either orange, purple or

303 pink.

304

305 *3.2. Registered Hypotheses*

306 1. **Shifted lognormal model.** We hypothesise that a shifted lognormal model

307 will give the best fit to our single-feature data, when compared to a lognor-

308 mal and a normal model.

309

310 2. **Log-linear effect of** *NT* **.** We will test the TCS model assumption that *NT*

311 has a log-linear effect by testing models with and without the log of this

312 term. We expect that this will confirm the results previously seen in papers

313 testing TCS i.e. that the log-linear approach will be best.

314

315 3. **Contrast model comparisons.** We will test the hypothesis proposed by

316 [(Buetti et al.,](#_bookmark30) [2019):](#_bookmark30) specifically, that the *collinear contrast integration*

317 *model* outperforms the *best feature guidance*, and *orthogonal contrast com-*

318 *bination models* for the calculation of *D*, by calculating and comparing the

319 mean absolute prediction error for each model.

320

321 4. **Reaction time predictions.** We will further test the hypothesis proposed by

322 [(Buetti et al.,](#_bookmark30) [2019)](#_bookmark30) by testing which model gives the best prediction at the

323 trial-by-trial RT level.

324 We will test each of these hypotheses by calculating the marginal likelihood

325 of the relevant models, and then calculating the posterior probabilities. This will

326 give us a probability for each model that represents the likelihood that the model

327 gives the best prediction. We will consider there to be evidence for one model over

328 the others if a given model has a probability above 90%. We will consider there

329 to be strong evidence for one model over the others if that model has a posterior

330 probability above 99%. This approach is most appropriate for our model: other

331 measures of model fit, such as AIC, require an assumption of flat priors (which is

332 not valid for multi-level models) and are based on point estimates (which is not

333 valid for Bayesian models) [(McElreath,](#_bookmark59) [2020).](#_bookmark59)

334 *3.3. Planned Explorations*

335 We plan to investigate the effect of individual differences in this paradigm:

336 to what extent performance in the single-feature task can predict performance in

337 the double-feature task for a given individual [(Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) were not able

338 to investigate this due to the between-subjects design of their study). We plan to

339 do this by specifying a more complex random effects structure for the model, that

340 allows for individual differences across different slopes for different features. This

341 allows us to then study the random effect correlation structure. However, given

342 these models can be challenging to fit, we will do this in an exploratory manner

343 after carrying out our formally registered analysis.

344 One of the benefits of using a multi-level modelling approach is that it is rel-

345 atively easy to extend to incorporate other factors that may contribute to reaction

346 times, such as eccentricity and inter-item distance, which may help to explain

347 behaviour further. To demonstrate this, we will also run exploratory analyses in-

348 cluding a factor for which ring the target is in to assess whether this improves

349 model fit or affects any of the conclusions that can be drawn from the model.

350 *3.4. Pilot Experiment*

351 Full details of a pilot experiment with *n* = 4 participants (960 trials each) using

352 our proposed analyses can be found in *Supplementary Materials - Pilot Analysis*.

353 This suggests that even with a small sample, we can convincingly demonstrate

354 H1 and H2. However, more data will be required to discriminate between the

355 models, particularly for H4. Given that our methods are within-subject, we have

356 reduced the number of trials per condition compared to [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) (12

357 in our pilot study, 20 in our proposed, compared to 40 in theirs). It is therefore

358 possible that the increased noise in our estimated *D* single-feature parameters will

359 make it more difficult to predict double-feature *D*s accurately. However, we think

360 this is unlikely to be the case as we can see that even in a small amount of pilot

361 data, we can verify H3, with the collinear model having the lowest mean absolute

362 prediction error.

# 363 4. General Methods

364 *4.1. Sample Size: Participants and Trials*

365 We tested 40 participants during the experiment. Our pilot experiment showed

366 that H1 and H2 are easily demonstrated with 10 times less data, and [Buetti et al.](#_bookmark30)

367 [(2019)](#_bookmark30) used 20 participants per experiment. Our sample size is therefore in line

368 with previous work testing H3 and H4. Ethical approval for the study was granted

369 by the University of Aberdeen (application number PEC/4677/2021/2).

370 Our pilot study above suggested that just 12 trials per condition may be suf-

371 ficient to fit our models. To be conservative, we proposed using 20 in our ex-

372 periment. We have demonstrated that using just half the data (20/40 trials per

373 condition) from [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) makes no difference to our computational

374 verification (see *Supplementary Materials - Computational Verification*).

0.003

700

650

reaction time

0.002

density

600

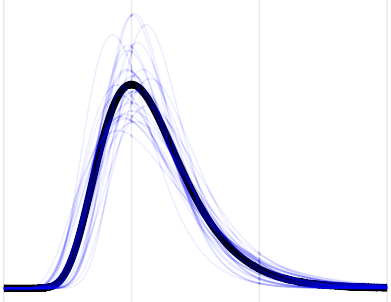
0.001

550

0.000

0

500



1000

1500

500

20 40 60

reaction time n

Figure 3: (left) The dark line shows the distribution we sampled from. The blue lines show distributions fitted to different samples of 20 data points. (right) Plot showing how the distribution of sample means vary with *n*. Shaded regions indicate the 50%, 80% and 95% confidence intervals.

375 Finally, we carried out a simulation experiment to estimate the confidence in-

376 tervals on the mean when sampling from a log-normal distribution. We defined

377 our distribution to have a mean-log of 6.135 and a standard deviation of 0.32.

378 These values were loosely based on the distributions of reaction times in [Buetti](#_bookmark30)

379 [et al.](#_bookmark30) [(2019).](#_bookmark30) The results are shown in Figure [3.](#_bookmark10) Based on these simulations, we

380 found that a sample of *n* = 20 led to a 95% confidence interval that is approxi-

381 mately 1.4 times larger than *n* = 40. We felt this was a suitable compromise given

382 that we collected our data within-subjects.

383 *4.2. Stimuli*

384 The targets and distractors were randomly assigned to the display based on

385 an invisible grid. Within each quadrant of the screen, there were three ’spokes’

386 each with four possible target positions (starting from the centre of the screen and

387 moving outwards), creating 36 different target positions in total, in three concen-

388 tric circles. A small amount of jitter was added to each possible position to make

389 the target locations less predictable.

390 **Distractor and target types:** we replicated the distractor types used in [Buetti](#_bookmark30)

391 [et al.](#_bookmark30) [(2019),](#_bookmark30) apart from that we changed one distractor colour (from blue to pink)

392 to allow us to discriminate better between different models of the data (see above).

393 There were six single-feature conditions (purple, orange and pink distractors and

394 triangle, circle and diamond distractors) and nine double-feature conditions (all

395 possible pairings of the single-feature conditions). The target was always a red

396 semicircle, except in the trials where the distractors were single-feature shapes

397 (triangles, circles and diamonds) in which case the target was a white semicircle.

398 **Set sizes:** we ran all the distractor set sizes used in [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) (1, 4,

399 9, 19 and 31). We also ran target-only ’zero distractor’ trials (60 in total, with 12

400 being the white semicircle target and the remainder the red semicircle target).

401 The experiments were programmed in PsychoPy and Pavlovia [(Peirce et al.,](#_bookmark73)

402 [2019).](#_bookmark73) Stimuli were pre-made to generate search array images with 1920 *×* 1080

403 resolution.

404 *4.3. Procedure*

405 Participants completed the experiment in the laboratory, sitting at a viewing

406 distance of 45cm from the screen (viewing distance will be fixed by using a chin

407 rest). They viewed a fixation cross before viewing a search array: they pressed

408 the space bar to continue to the trial. Participants were told to search for the

409 target among distractors (either a red semicircle or a white semicircle, depend-

410 ing on the block) and report if the semicircle target pointed to the left or right, by

411 pressing either the left or right button on a button box (Cedrus RB-540). They first

412 completed 16 practice trials where they received feedback immediately after com-

413 pleting each trial. In the real experimental trials, participants received feedback

414 on their average accuracy and reaction time after each block of 320 trials. Partic-

415 ipants completed 5 blocks of trials (1600 trials overall i.e. 320 trials in each of 5

416 experiments, consisting of 5 set sizes x 3 distractor conditions x 20 repeats + 20

417 zero distractor trials). The trials where the distractors were single-feature shapes

418 (i.e. the target was a white semicircle - Experiment 1b in [Buetti et al.](#_bookmark30) [(2019))](#_bookmark30) all

419 appeared in one block (which appeared at a randomly selected position within the

420 experiment). All other trials (where the target was red semicircle) were fully ran-

421 domised i.e. all different conditions were completely intermixed. This approach

422 was taken as TCS requires the participant to have a well-defined target template

423 in mind in order to compare this to the stimuli in the display. Thus, participants

424 were cued to search for the relevant target at the beginning of each block.

425 In both the practice and experimental trials, the search display always re-

426 mained on screen until a response was made, or until 5 seconds had passed.

427 *4.4. Data Pre-processing*

428 Only participants who complete the full experiment were considered candi-

429 dates for inclusion in the data analysis. We applied the same inclusion criteria as

430 the original paper: participants were only included if their search accuracy was

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over 90% and their average response time was not smaller or larger than two stan- dard deviations from the group average response time.

For participants included in the analysis, we applied the data cleaning used in the pilot data analysis i.e. removing incorrect trials and removing the top and

[2](#_bookmark13)

435 bottom 1% of their data.

436 *4.5. Analysis Plan*

437 All analysis was carried out using R (v4.2.0), brms (v2.17.0) and rStan (v2.26.11)

438 As discussed above, we used mixed-effect models with either normal, lognormal

439 or shifted lognormal distributions.

440 Please see the analysis of our pilot data for a full implementation of our anal-

441 ysis pipeline, including all code (available on Github at [https://github.com/](https://github.com/Riadsala/single_double_feature_search)

442 [Riadsala/single\_double\_feature\_search](https://github.com/Riadsala/single_double_feature_search)).

443 *4.6. Registered Report*

444 The original Stage 1 registered report for this manuscript is available at [https:](https://osf.io/f9sua/)

445 [//osf.io/f9sua/](https://osf.io/f9sua/). All study data, materials and analysis code for both Stage 1

446 and Stage 2 are available at [https://github.com/Riadsala/single\_double\_](https://github.com/Riadsala/single_double_feature_search)

447 [feature\_search](https://github.com/Riadsala/single_double_feature_search).

448 We report how we determined our sample size (see Section [4.1),](#_bookmark9) all data exclu-

449 sions (if any), all inclusion/exclusion criteria, whether inclusion/exclusion criteria

450 were established prior to data analysis (see Section [4.4)](#_bookmark12) all manipulations, and all

451 measures in the study (see Section [4.2).](#_bookmark11)

452 **5. Results**

453 All 40 participants had accuracy over 90% (minimum 93*.*1%). One participant

454 had an average response time (1100ms) over two standard deviations from the

455 group average response time (781ms) and was removed. Incorrect trials were

456 then removed, and the data was trimmed (only including response times between

457 the 1% and 99% quantiles) leaving us with 39 participants completing a total of

458 59,587 trials.

2Please note that incorrect trial removal was in the analysis plan as outlined in the Supplemen- tary Materials, but was accidentally omitted from the Stage 1 text.

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All Bayesian models were fit to the new data using exactly the same proce-

[3](#_bookmark14)

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dure as the pilot data presented in the Stage One review process. We checked

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for convergence of our models by visually inspecting the chains as well as ver- ifying that the *R*ˆ was close to 1 for all parameters of all the fitted models (see *Supplementary Material - Main Analysis* for full model fit information).

* 1. *Hypothesis 1: Shifted-lognormal model*

Our first hypothesis concerns which distribution best fits the single feature response time data. We fit multi-level models with a i) normal, ii) lognormal, and

iii) shifted-lognormal distribution. The models all used the same model formula that estimated search slopes in terms of log *Nt* for each feature. Maximal random effect structures were used.

After each of these models had been fit to the data, leave-one-out (LOO) model

comparison was used to calculate posterior probabilities for each. The results of this procedure allocated *∼* 100% of the weight to the shifted-lognormal model, so we can conclude that, in accordance with our registered hypothesis, it is the best

distribution (out of the three we tested[4](#_bookmark15)) to use for modelling response times in this paradigm. This model is shown in Figure 2.2 of the *Supplementary Materials*

*- Registered Analysis*.

* 1. *Hypothesis 2: log-linear effect of NT*

We then used the same methods to verify that using log *NT* for the search slope does indeed give a better fit to the data than simply using *NT* . The results are again

conclusive with *∼* 100% of the model weight being assigned to the model that is

log-linear in *NT* , again in accordance with our original hypothesis.

* 1. *Hypothesis 3: Contrast Model Comparison*

Now that we have confirmed that the shifted-lognormal multilevel model (with a log-linear effect of *NT* ) is indeed the best fit to the data we will extract the search slopes for each feature. These are summarised in Table [3.](#_bookmark16) We can see that we have successfully obtained a range of values for both *Dc* and *Ds*. As with [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) we find that the values for *Ds* are larger than *Dc* (see Table [2),](#_bookmark3) meaning that search slopes for colour features are shallower than shape.

3The only departure was an increase in iterations from 5000 to 80000 for the model predicting reaction times, based on advice given in the Stan forums, to enable the bridge sampling process to work properly.

4See discussion for Wald, Weibull, etc.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| feature | *Dc* | 95%HDCI | feature | *Ds* | 95%HDCI |
| orange | 0.156 | [0.139 , 0.173] | triangle | 0.253 | [0.230 , 0.275] |
| pink | 0.042 | [0.028 , 0.057] | diamond | 0.187 | [0.171 , 0.205] |
| purple | 0.015 | [0.002 , 0.030] | circle | 0.191 | [0.175 , 0.204] |

Table 3: A summary of the posterior estimates of *Dc* and *Ds* values from our Experiment. Note that our values are reported in seconds, in contrast to Table [2,](#_bookmark3) which follows [(Buetti et al.,](#_bookmark30) [2019)](#_bookmark30) and reports the slopes in milliseconds.

489 We now combine the *single-feature* search slopes, *Dc* and *Ds*, to predict the

490 *double-feature* conditions (*Dc,s*) using Equations [2,](#_bookmark4) [3](#_bookmark5) and [4](#_bookmark6) and above. The results

491 are summarised in Figure [4.](#_bookmark17) We find that while the collinear contrast model has

492 the highest *R*2 (0.922, compared to *R*2 = 0*.*884 for best feature, and *R*2 = 0*.*916 for

493 orthogonal contrast), the orthogonal contrast model is the most accurate, both in

494 terms of mean absolute error (0.165, compared to 0.185 for best feature and 0.271

495 for collinear) and having a regression slope closest to 1 (1 compared to 0.753 and

496 1.48). Therefore, Hypothesis 3 does not hold: orthogonal contrast rather than

497 collinear contrast offers the best prediction of search slopes in the double-feature

498 condition.

best feature collinear orthogonal contrast

*y* = 0.0225  0.753 *x*, *R* 2 = 0.8844 *y* = 0.00808  1.48 *x*, *R* 2 = 0.9221 *y* = 0.0158  1 *x*, *R* 2 = 0.9157

0.15

0.15

0.15

0.10

De

0.10

0.10

0.05

0.05

0.05

0.00

0.00

0.00

0.00 0.05 0.10 0.15 0.000 0.025 0.050 0.075 0.100 0.00 0.05 0.10 0.15

Dp

Figure 4: Predicting *Dc,s* from *Dc* and *Ds*. The *x*-axis shows our predictions, *Dp*, using the best feature, collinear contrast, and orthogonal contrast models.

499 *5.4. Hypothesis 4: Reaction Time Predictions*

500 Upon reflection, the approach to model comparison we outlined in our reg-

501 istered analysis was limited in a number of ways. Our original plan was to use

502 the posterior predictions from a model trained on the single-feature data to act

503 as a prior for the double-feature data. While we initially thought this would be

504 an elegant approach, there are a large number of parameters that are outside the

505 main focus of this paper yet still require priors (intercepts, group level variance

506 and residual variance). Furthermore, while the methods for estimating *Dc,s* pre-

507 sented above give good predictions in terms of the mean value, it is not clear

508 that the standard deviation for these distributions will be accurate. As such, we

509 have developed a new, simpler method for this final comparison. To maintain full

510 transparency, we present both methods here.

511 *5.4.1. Registered Method*

512 Our final hypothesis concerns how well the different feature combination mod-

513 els perform when predicting reaction times. We find very little difference between

514 the three methods in terms of LOO model weights: 0.318 for best feature, 0.346

515 for collinear and 0.336 for orthogonal contrast. Thus, according to this analysis,

516 we find no conclusive answer to hypothesis 4: all models give similar predictions

517 at the trial-by-trial RT level.

518 *5.4.2. Updated Method*

519 Our new method for exploring this hypothesis involves taking *n* = 100 sam-

520 ples of the fixed effects from both the model fitted to the single-feature data and

521 the model fitted to the double-feature data. Each of these samples includes an

522 intercept (*a*), slope (*D*), non-decision time (ndt), and residual variance (*σ* ). We

523 then take the parameters from the double-feature model, but replace the *D* values

524 with our predicted *D* using the single-feature model. Finally the predicted mean

525 log(*rt*) is calculated for each feature and number of distractors. These are then

526 compared to the empirical reaction times and we compute the absolute error.

527 We can also calculate an upper-bound by carrying out the above process, but

528 without replacing the fitted *Dc,s* with the predicted. This allows us to report ‘rel-

529 ative absolute error’. As all of the methods under consideration make identical

530 predictions for trials with no distractors, these are omitted from this calculation.

531 The results of this procedure are in-line with the registered analysis presented

532 above: all three methods perform well relative to our baseline (see Table [4),](#_bookmark18) and

533 thus we cannot make any strong conclusions related to hypothesis 4. All three

534 contrast combination methods do a good job of accounting for the reaction time

535 data collected.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| metric | abs error | | |  |
|  | lower | median | upper |  |
| orthogonal | 0.994 | 1.00 | 1.02 |
| collinear | 0.990 | 1.01 | 1.05 |
| best feature | 0.999 | 1.01 | 1.02 |

Table 4: How well can we predict RTs using *Dp* (collinear, best feature or orthogonal contrast) comped to using *De*? A value of 1 means that our estimates of *D* derived from the single-feature trials does an equally good job at predicting the double-feature trials as using the *D* fit to the data.

# 536 6. Planned Explorations

537 Our interpretation of the null/neutral results for Hypothesis 4 (the prediction

538 of reaction times) is that the differences in predictions from the three contrast

539 combination methods are small relative to the (i) individual differences between

540 participants and (ii) trial-to-trial variability due to target eccentricity. Thus, in our

541 exploratory analysis, we investigate how incorporating these factors affects our

542 conclusions.

543 *6.1. Individual Differences*

544 We start this exploratory analysis looking at how the *Dc* and *Ds* values vary

545 from participant to participant. From Figure [5](#_bookmark19) (*left*) we can see that there is con-

546 siderable variation between observers - in fact, the variation from one observer

547 to the next is often larger than the variation across features. To investigate this

548 further we calculated the correlations between each of the features, by calculating

549 Pearson’s *r* for each sample from our posterior, which gives us a full posterior dis-

550 tribution for the correlations. We can see in Figure [5](#_bookmark19) (*right*) that while both the *Dc*

551 and *Ds* are correlated within feature classes (*∼* 0*.*75), there is no correlation of any

552 of the colour features with any of the shape features. The individual differences

553 for the *double-feature* conditions are much less pronounced - these conditions are

554 easy and the search slopes are quite close to flat. Hence, the correlations are all

555 much weaker, presumably due to range restriction.

556 Given these results, it is perhaps unsurprising that our analysis for Hypothesis

557 4 leads to an inconclusive result for distinguishing between the three contrast com-

558 bination methods. Perhaps taking these individual differences into account when

559 we predict reaction times will lead to improved power to discriminate between

560 the models. However, before we do so, we will also investigate incorporating

561 information about target eccentricity into the model.

circle triangle diamond

feature

pink purple orange

0.0 0.2 0.4

Dc and Ds

1.0

0.5

Pearson's correlation coefficent

0.0

−0.5

1.0

0.5

0.0

−0.5

pink purple orange diamond triangle circle

pink purple orange diamond triangle circle

pink purple orange diamond triangle circle

pink purple orange

diamond triangle circle

Figure 5: Individual differences in *Dc* and *Ds*. (*left*) Posterior probability distributions for *Dc* and

*Ds* for each individual. (*right*) Estimated correlations between each of the *Dc* and *Ds*.

562 *6.2. Target Eccentricity*

563 It is well known that there are eccentricity effects in visual search, with reac-

564 tion times being longer for targets that are further away from fixation [(Carrasco](#_bookmark31)

565 [et al.,](#_bookmark31) [1995;](#_bookmark31) [Wang et al.,](#_bookmark82) [2017).](#_bookmark82) To investigate this in our dataset, we will use the

566 same methods as above (fitting a multi-level shifted-lognormal model) but now

567 including an additional factor that represents how far the target was from the fix-

568 ation cross. This is coded as a three-level categorical factor representing which

569 ring contained the target (see stimulus details, above). Allowing for interactions

570 with the *feature* and log *NT* increases the number of fixed effect parameters in the

571 model from 8 to 22, with the model equation becoming the following:

*y ∼* 0 + *r* + *r* : *f* : log(*NT* ) + (1*|id*) (5)

572 We experimented with including *r* in the random effect structure, but this

573 proved difficult to fit. We also had to revise the priors used in our registered anal-

574 ysis, in order to lower the intercept. Full details can be found in *Supplementary*

575 *Materials - Planned Explorations*.

576 After obtaining a model that passed all convergence checks, we examined the

577 posterior distribution for the effect of *ring*. Figure [6](#_bookmark20) paints an interesting and

578 complex picture in which some features (e.g. some colours, particularly those

579 that are more distinct from the target colour) are clearly leading to ‘pre-attentive

580 search‘ in which response times are unaffected by either the number of distractors

581 or target eccentricity. However, shape features seem to be strongly affected by

582 eccentricity, particularly when there are multiple distractors in the stimulus.

orange purple pink

1.4

Predicted response time (sec)

1.2

1.0

0.8

diamond triangle circle

1.4

1.2

1.0

0.8

ring

1

2

3

0 1 2 3 0 1 2 3 0 1 2 3

Log number of distractors

Figure 6: Fixed effects for predicting the effect of ring, feature and number of distracters on response times. Shaded regions represent the 53% and 97% HDCIs. We can see that *ring* has an effect on search slopes, and that this effect is more pronounced for some features (i.e., triangles) than others.

583 We can now compute our predictions (*Dp*) for *Dc,s* taking the *ring* into ac-

584 count. Doing so leads us to a similar result as before with orthogonal contrast

585 outperforming the best feature and collinear measures in terms of absolute error

586 (0.023 compared to 0.025 (best feature) and 0.034 (collinear)). However, the re-

587 gression slopes are all relatively similar (0.90 for best feature, 1.58 for collinear

588 and 1.15 for orthogonal contrast). Thus, adding ring into the model does not dras-

589 tically change our overall conclusions, with the orthogonal contrast model still

590 giving the best prediction of search slopes in the double-feature condition.

591 *6.3. Predicting Response Times*

592 We will now test to see if we can discriminate between the three contrast

593 combination methods when we take target eccentricity (ring) and individual-level

594 slopes into account. We use the same model comparison as before (see *Supple-*

595 *mentary Materials - Planned Explorations* for full code) and find orthogonal con-

596 trast performs best, closely followed by best feature.

597 *6.3.1. Issues with the Collinear Contrast method*

598 In the previous model, the upper bound on the error in the collinear contrast

599 method is high (see Table [5).](#_bookmark21) To explain this, we can look back at Equation [4:](#_bookmark6)

600 when search slopes are close to 0, it is possible that we will observe negative

601 values in the empirical data. Breaking down our data to compute search slopes

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| metric | abs error | | |  |
|  | lower | median | upper |  |
| orthogonal | 1.01 | 1.00 | 1.04 |
| collinear | 1.03 | 1.00 | 5.15 |
| best feature | 1.03 | 1.00 | 1.07 |

Table 5: How well can we predict RTs using *Dp* (collinear, best feature or orthogonal contrast) comped to using *De* when using a model containing the ring of the target? A value of 1 means that our estimates of *D* derived from the single-feature trials does an equally good job at predicting the double-feature trials as using the *D* fit to the data.

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for each person and each target eccentricity increases the chances of this being observed. Looking at Equation [4](#_bookmark6) we can see that in the case where both *D*1 and *D*2

are small but one is negative (i.e. *D*1 *∼ −D*2), then 1*/D*1 + 1*/D*2 *∼* 0. This leads

to our estimated *D* = 1 *>>> D*1*, D*2 i.e. our estimated D is much larger

1*/D*1+1*/D*2

than the slopes that were used to generate it, which is clearly incorrect. However, we do note that the main conclusions of our analyses still hold even if we remove these negative slopes (by restricting our analyses only to certain colours and rings of the data - see *Supplementary Materials: Suggestions from Reviewers* for more details), suggesting that addressing this mathematical issue may not necessarily lead to the collinear contrast method being preferred.

# 612 7. General Discussion

613 In this paper, we aimed to test the extent to which the results of [Buetti et al.](#_bookmark30)

614 [(2019)](#_bookmark30) replicate and generalise, using a new modelling approach. Our results

615 allow us to confirm our pre-registered hypotheses 1 and 2. Firstly, a shifted-

616 lognormal distribution of response times outperforms normal and lognormal dis-

617 tributions, demonstrating that reaction time data are best modelled by a skewed

618 distribution with an offset. Similarly, we confirmed that the number of distractors

619 has a log-linear effect in this model, in line with the predictions of TCS theory.

620 We also replicated other aspects of the original [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) paper with

621 a different experimental set up, such as to observing shallower search slopes for

622 colour features compared to shape features.

623 We do not find support for our pre-registered hypotheses 3 and 4. For pre-

624 dicting *D* in the double-feature conditions, our analyses found that the orthogonal

625 contrast model was favoured over collinear, which is not in line with the regis-

626 tered hypothesis, which predicted that the collinear contrast model would be best

627 (in line with [Buetti et al.](#_bookmark30) [(2019)).](#_bookmark30) Similarly, for hypothesis 4, we found that

628 there was relatively little difference between the three combination methods for

629 prediction of trial-by-trial reaction times. Our exploratory analyses suggest that

630 incorporating additional factors (e.g. individual differences in participant *Dc* and

631 *Ds* values, and the eccentricity of the target) allows better discrimination between

632 models, but again suggests that the orthogonal contrast combination method gives

633 the best predictions.

634 *7.1. Modelling of reaction times*

635 In much of the literature on visual search, mean reaction times are modelled

636 using a simple linear model *y*¯ = *bNT* + *a* (e.g. [Treisman and Gormican](#_bookmark79) [(1988);](#_bookmark79)

637 [Rosenholtz et al.](#_bookmark76) [(2012);](#_bookmark76) [Hughes et al.](#_bookmark40) [(2016)).](#_bookmark40) The *b* coefficients are often re-

638 ferred to as “search slopes” and are often treated as measurements of theoretical

639 importance. Our results indicate that a shifted-lognormal model that is loglinear

640 in *NT* offers a much better fit to the data (log(*y*) *− ndt* = *b* log(*NT* ) + *a*), which

641 is perhaps not surprising, given the properties of reaction time data, where valid

642 responses normally begin at around 100ms, and the distribution often has a long

643 “tail” of slower responses.

644 However, there have been concerted efforts within the literature to model re-

645 action time distributions more effectively: indeed, [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) use log *NT*

646 when computing their search slopes. In terms of reaction time distributions, log

647 transformations are frequently taught as a way to normalise reaction time data (al-

648 though often with caveats regarding how this can change the interpretation of the

649 results e.g. [Osborne](#_bookmark70) [(2002))](#_bookmark70) and are frequently used in analysing reaction time

650 data e.g. [(Clarke et al.,](#_bookmark34) [2022b).](#_bookmark34) Researchers have also looked at other distribu-

651 tions to assess which offer the best fit to empirical response times in visual search.

652 For example, [Palmer et al.](#_bookmark71) [(2011)](#_bookmark71) compared ex-Gaussian, ex-Wald, Gamma, and

653 Weibull distributions and found that the distributions with exponential compo-

654 nents offer a better fit to the data. Our results are in line with this. However,

655 we opted to use a shifted-lognormal distribution in our analysis above for mostly

656 pragmatic reasons, as these more complex distributions are often computationally

657 difficult to fit[5](#_bookmark22). It has also been argued that trying to select a “correct” distribu-

658 tion is likely to be problematic for empirical data, which is probably a mixture

659 of multiple components [(Wolfe et al.,](#_bookmark89) [2010).](#_bookmark89) Similarly, some recent approaches

660 make use of drift-diffusion methods (e.g. [Wolfe and Van Wert](#_bookmark87) [(2010);](#_bookmark87) [Yu et al.](#_bookmark91)

661 [(2022);](#_bookmark91) [Corbett and Smith](#_bookmark35) [(2020)),](#_bookmark35) though again these models can be challenging,

5See: https://discourse.mc-stan.org/t/model-fails-to-converge-when-using-brms/9062

662 particularly when considering how to interpret the parameters [(Evans and Wagen-](#_bookmark37)

663 [makers,](#_bookmark37) [2019;](#_bookmark37) [Bompas et al.,](#_bookmark28) [2023).](#_bookmark28) While important, these debates are outside

664 the scope of the present Registered Report.

665 Despite these previous findings, the use of linear search slopes is still prevalent

666 in the visual search literature. Our work shows that these choices of distribution

667 can influence results and conclusions (see section [7.2](#_bookmark23) below), and therefore we

668 recommend that other researchers consider carefully how they want to model their

669 data. Even in the case where the search slopes are the primary outcome measure

670 of interest (as opposed to the potentially more ’cognitive’ parameters of e.g. Wald

671 distributions, or drift diffusion models), we demonstrate that approaches that bet-

672 ter account for the data distribution can be taken with relative ease. While trying

673 to decide on the best model may be a challenging task, our view is that the better

674 the underlying statistical model does in accounting for the data, the more credence

675 we can give to the inferences we draw from model parameters such as the slope.

676 *7.2. Discriminating between combination methods*

677 In [Buetti et al.](#_bookmark30) [(2019),](#_bookmark30) the collinear contrast integration model was found to

678 provide the best fit for their data, providing a more precise prediction than the

679 orthogonal contrast combination model (as measured by both the closeness of

680 the slope of the regression line to one, and the mean average prediction error).

681 Accepting this model of how the combination process works has theoretical im-

682 plications e.g. it implies that colour and shape contrasts independently contribute

683 to attentional guidance. However, we did not find strong support for this model,

684 instead finding that the orthogonal contrast combination model provides the best

685 fit with the data.

686 One possibility is that our small modifications to the experimental stimuli

687 changed the strategy that participants used. However, this seems unlikely given

688 that we only made changes to the colour of the stimuli (see Table [6),](#_bookmark24) a manip-

689 ulation that [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) also used, with no changes to their overall con-

690 clusions, although it is of course possible that different colour combinations may

691 lead to (for example) different relative saliences, which could change the com-

692 bination method used by the participant. However, our reanalysis of the original

693 [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) data using our new methods also suggested that the orthogonal

694 contrast model was best supported. Thus, we suggest that the choice of modelling

695 distribution (e.g. shifted-lognormal v.s. lognormal) affects the conclusions drawn,

696 and thus we should aim to use the models that best align with the data in order to

697 better understand the theoretical implications of our findings.

|  |  |  |  |
| --- | --- | --- | --- |
| colour | L | a | b |
| orange | 66.7 | 30.5 | 86.5 |
| purple | 24.6 | 2.8 | -17.5 |
| pink | 60.2 | 44.2 | -44.5 |
| red | 52.2 | 78.8 | 76.2 |

Table 6: CIELAB colour values used for targets and distractors in the experiment.

698 We also modified the way stimuli were presented in our experiment com-

699 pared to [Buetti et al.](#_bookmark30) [(2019):](#_bookmark30) rather than running each experiment separately, we

700 (mostly) intermixed conditions. Models of attention presume that we hold a target

701 template in our memory [(Duncan and Humphreys,](#_bookmark36) [1989),](#_bookmark36) and thus we ensured

702 that the trials where the target was the white semicircle were blocked separately

703 from the trials where the target was the red semicircle, to try to avoid conflict be-

704 tween maintaining multiple target templates in memory. However, it is possible

705 participants used strategies such as shifting the target representation away from the

706 distractors, or generally using relational strategies [(Navalpakkam and Itti,](#_bookmark65) [2007;](#_bookmark65)

707 [Becker,](#_bookmark26) [2010;](#_bookmark26) [Yu et al.,](#_bookmark92) [2023),](#_bookmark92) which would be more challenging in our experi-

708 mental set up where participants viewed a larger number of distractors compared

709 to [Buetti et al.](#_bookmark30) [(2019).](#_bookmark30) In relation to the models, this type of target representation

710 shift could occur more strongly for one feature dimension (e.g. colour) than the

711 other, perhaps changing the relationship between the contrasts for different fea-

712 ture dimensions and therefore the preferred model. If future work were to confirm

713 this hypothesis, it would suggest that observers are able to cognitively shift their

714 strategy based on the information available in the task.

715 Another possibility is that because some participants had negative search slopes,

716 the collinear contrast model predicts implausibly large reaction times, due to the

717 mathematical formulation of this model, leading to worse predictions. Despite the

718 fact that our exploratory analyses suggested that removing these negative slopes

719 would not change our conclusions, we suggest that a future improvement for the

720 collinear contrast integration model would be to modify it to be able to give sen-

721 sible predictions in these situations, given that negative search slopes do occur in

722 some situations [(Utochkin,](#_bookmark81) [2013;](#_bookmark81) [Rangelov et al.,](#_bookmark75) [2017).](#_bookmark75)

723 Finally, we would argue that it is difficult from these results to definitively

724 make a decision about which model is best: all three models give very similar

725 predictive weights during our model evaluation process. One challenge is that

726 in general, the double feature searches are easy, and therefore the search slopes

727 are fairly flat and there is not much variability to allow different models to make

728 different predictions. For the current paradigm, a fruitful approach for future re-

729 search could be to consider using different feature sets, and in particular, moving

730 away from colour as feature, which may be a particularly salient cue (see Section

731 [7.2.3](#_bookmark25) below).

732 *7.2.1. Individual differences*

733 Our (planned) exploratory analysis of the individual differences in search slopes

734 suggests that there are large differences from one observer to the next. Indeed

735 in some cases, these are larger than the differences from one feature to another.

736 The difference between the steepest and shallowest search slopes (fixed effects) is

737 0.238 (*Dtriangle* = 0*.*253, while *Dpurple* = 0*.*015). If we compare this to the range

738 of observer search slopes within a feature, we find this varies from 0.242 (*Dtriangle*

739 per-observer ranges from 0.395 to 0.152) to 0.149 (*Dpink* ranges from -0.065 to

740 0.092). This suggests a challenge for modelling based on average performance:

741 can we be sure that averages represent a meaningful summary of the data, given

742 that we see very clear individual differences? It could certainly be argued that ob-

743 servers might be using different strategies, and thus some members of the sample

744 population might use (for example) a collinear combination strategy, while oth-

745 ers use an orthogonal contrast strategy (and we can see some hints of this when

746 we plot the predictions of *D* separately for each participant in the *Supplementary*

747 *Materials - Planned Explorations*). Variable strategies have been found for other

748 search behaviour [(Clarke et al.,](#_bookmark33) [2022a;](#_bookmark33) [Kristja´nsson et al.,](#_bookmark50) [2014;](#_bookmark50) [Proulx,](#_bookmark74) [2011;](#_bookmark74)

749 [Li et al.,](#_bookmark52) [2022),](#_bookmark52) highlighting the importance of considering individual differences

750 when understanding behaviour.

751 We also found that search slopes were correlated within feature, but not be-

752 tween: i.e, knowing that an observer’s search slope for a colour condition allows

753 us to predict their search slopes for the other colour conditions, but not any of

754 the shape conditions. However, given the block design of our experiment, it is

755 possible that this reflects a type of priming effect: knowing the search slope for

756 a feature in the first block tells allows us to predict the search slopes of the other

757 features in that block, but tells us nothing of the observer’s behaviour in the sec-

758 ond block. Post-hoc analyses looking at correlations within the colour condition

759 by block suggest that this seems unlikely to explain our results fully, as we still

760 observe good correlations between different colour search slopes across blocks

761 (see *Supplementary Materials - Suggestions from Reviewers* for further details).

762 However, to test this fully we would need to design the experiment differently in

763 order to avoid block confounds, allowing us to disentangle whether these corre-

764 lations reflect something about an observer’s behaviour with different features, or

765 instead how an observer’s behaviour changes over time.

766 *7.2.2. Eccentricity*

767 [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) argues that the processing undertaken in this type of task

768 can be done in parallel, with observers using peripheral vision to distinguish be-

769 tween target and distractors, and that there is systematic variation in reaction times

770 as a function of set size associated with parallel processing. Target Contrast Sig-

771 nal Theory incorporates eccentricity effects into this type of parallel processing

772 via a time-out parameter (*T*0) [(Lleras et al.,](#_bookmark56) [2020;](#_bookmark56) [Wang et al.,](#_bookmark83) [2018;](#_bookmark83) [Ng et al.,](#_bookmark67)

773 [2018).](#_bookmark67) Here, we confirm in our exploratory analyses that we are able to detect

774 relatively strong eccentricity effects, as a model with target ring number included

775 was a better predictor of the data than one without. However, including this factor

776 did not change our overall conclusions about which model best predicted *D* in the

777 double-feature condition, or which model best predicted reaction times.

778 In our experiment we followed [Buetti et al.](#_bookmark30) [(2019)’](#_bookmark30)s original methods, with

779 participants freely viewing the displays. It is therefore likely that in some cases,

780 observers felt that peripheral information was insufficient to make judgements,

781 and thus made eye movements, moving into a more serial, focused-attention pro-

782 cessing stage. Future work could more exclusively investigate peripheral effects

783 in parallel processing by ensuring fixation when viewing the displays.

784 *7.2.3. Limitations*

785 One limitation of the experimental approach may be the feature dimensions

786 chosen. We kept these the same as in [Buetti et al.](#_bookmark30) [(2019)](#_bookmark30) (colour and shape), but

787 there is good evidence that colour may in some ways be a ’basic’ feature dimen-

788 sion that is particularly salient, especially in peripheral vision, whereas guidance

789 of attention by shape may be more complex [(Wolfe,](#_bookmark86) [2021).](#_bookmark86) Mathematically, it

790 would be better to have features where the slope values across the two dimensions

791 are more similar, as all of the contrast combination formulae essentially consist of

792 sums of inverse values, and if the slope values are highly dissimilar, the inverse

793 sums will be disproportionately determined by one feature. This may indeed re-

794 flect how participants are approaching this task, as it may be the case that they

795 preferentially attend to the more discriminating feature (colour) and the contribu-

796 tion of shape to their behaviour in the double-feature condition may be negligible.

797 However, for the purposes of discriminating between the models, it would be ben-

798 eficial in future experiments to adjust the target set, perhaps by making the shape

799 dimension more salient (e.g. by increasing the size of the targets), or by selecting

800 a different pair of features (e.g. shape and orientation).

801 *7.3. Conclusions and future directions*

802 In the current paper, we have independently reproduced the findings of [Buetti](#_bookmark30)

803 [et al.](#_bookmark30) [(2019)](#_bookmark30) by extending their modelling to a multi-level framework. We have

804 used a Bayesian approach, but note that this is in many ways entirely arbitrary: all

805 of the modelling decisions we have taken would be possible within a frequentist

806 framework as well. We also aimed to replicate the previous findings by running

807 a within-subjects experiment, and broadly find that the Target Contrast Signal

808 Theory does a good job of predicting the data. When using single-feature search

809 slopes to predict double-feature search slopes, we do not replicate the previous

810 finding that the collinear contrast integration method outperforms other options,

811 but instead find that all combination methods do reasonably well, and in this par-

812 ticular experimental design, it may be difficult to conclusively distinguish between

813 them.

814 One of the clear benefits of Target Contrast Signal Theory [(Lleras et al.,](#_bookmark56) [2020)](#_bookmark56)

815 is its quantitative nature, allowing it to be empirically tested in a straightforward

816 manner. Here, we demonstrate that we can independently replicate many aspects

817 of TCS, while also offering extensions to the model that we hope will stimulate

818 more research and refinement of this theory. Some suggestions for possible future

819 directions and hypotheses that could be tested include:

820 1. It is relatively straightforward to make predictions about the mean reaction

821 time per participant in the double-feature search condition: however, we

822 have not attempted to predict an individual’s trial-to-trial variance for dif-

823 ferent features, which could improve the model fit further.

824

825 2. We find correlations within feature classes (i.e. *Dc* and *Ds*) but not between:

826 however, these may be a side-effect of the block design of the experiment.

827 A future experiment could randomise trial type in order to more fully un-

828 derstand the nature of these correlations.

829

830 3. To more fully explore which combination model best predicts the data, we

831 suggest a) modifying the collinear contrast model to accommodate negative

832 search slopes b) attempting to find experimental conditions that best dif-

833 ferentiate between the models, perhaps by using feature dimensions other

834 than colour and c) modifying the experimental design to enforce parallel

835 processing e.g. by making the display gaze contingent.

836 Computational modelling approaches alongside detailed, quantitative theory

837 building has been argued to be one way to improve the reliability of psycho-

838 logical research [(Oberauer and Lewandowsky,](#_bookmark69) [2019;](#_bookmark69) [Guest and Martin,](#_bookmark39) [2021).](#_bookmark39)

839 By combining this approach with fully open datasets and analysis scripts, we

840 can hopefully begin to take a more “distributed collaborative network” approach

841 [(Moshontz et al.,](#_bookmark64) [2018)](#_bookmark64) to our scientific questions. As such, we would like to

842 conclude by encouraging other researchers to critique, build on and improve the

843 approach we have taken in this manuscript, in order to further improve our ability

844 to model performance in visual search tasks.

# 845 Conflict of interest

846 The authors declare that they have no conflict of interest.

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