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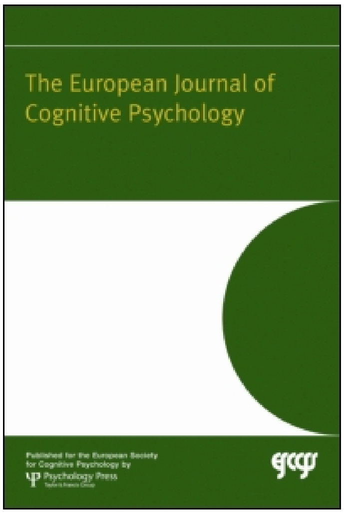

European Journal of Cognitive Psychology
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713734596

SOLAR versus SERIOL revisited

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First published on: 12 March 2010

To cite this Article Davis, Colin J.(2010) 'SOLAR versus SERIOL revisited', European Journal of Cognitive Psychology, 22: 5, 695 — 724, First published on: 12 March 2010 (iFirst)
To link to this Article: DOI: 10.1080/09541440903155682
URL: http://dx.doi.org/10.1080/09541440903155682

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EUROPEAN JOURNAL OF COGNITIVE PSYCHOLOGY
2010, 22 (5), 695–724

Psychology Press
Taylor & Francis Group

SOLAR versus SERIOL revisited

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This paper compares two approaches to modelling orthographic processing, the Self-Organising Lexical Acquisition and Recognition (SOLAR; Davis, 1999, in press) and the Sequential Encoding Regulated by Inputs to Oscillating Letter units (SERIOL; Whitney, 2001, 2004) models, following up on a previous analysis by Whitney (2008). I provide a brief overview of the SOLAR model, and its key similarities to and differences from the SERIOL model, focusing in particular on the different mechanisms underlying the formation of the positional gradient in the two models. I also discuss the neural implementation of the SOLAR model's lexical matching algorithm, and its plausibility. In the final part of the paper I discuss empirical attempts to adjudicate between the two models, focusing on the masked form priming paradigm, as well as the use of theoretical match values to test model predictions. It is concluded that the SOLAR model provides an account of visual word identification that is neurally plausible and that succeeds in explaining critical orthographical similarity data, but that the SERIOL model does not satisfy these constraints.

Keywords: SOLAR; SERIOL; Visual word recognition; Letter position coding; Computational models.

The way in which letter position is coded within a word has attracted considerable theoretical and empirical interest in recent years (see, for example, a recent issue of *Language and Cognitive Processes* devoted to "cracking the orthographic code", edited by Grainger, 2008). This topic is of interest both in the context of achieving a better understanding of reading, as well as from a broader perspective of understanding fundamental issues such as how the brain binds together different aspects of an object (such as identity and position), how stimuli in the world are transformed into neural codes, and how these codes are compared to previously learned codes.

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This research was partially supported by ESRC Grant RES-000-22-2662 to Marc Brysbaert and Colin J. Davis. I would like to thank Samantha McCormick for her assistance in the preparation of the manuscript, and Jeff Bowers, Jonathan Grainger, Steve Lupker, Manuel Perea, Nikki Pitchford, Yuri Saalman, and Marcus Taft for their comments on earlier drafts of this paper.

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http://www.psypress.com/ecp DOI: 10.1080/09541440903155682

The present theoretical note provides a comparison of two approaches to modelling orthographic processing, the Self-Organising Lexical Acquisition and Recognition (SOLAR; Davis, 1999) and the Sequential Encoding Regulated by Inputs to Oscillating Letter units (SERIOL; Whitney, 2001, 2004) models, following up on a previous analysis by Whitney (2008). I start by providing a brief overview of the SOLAR model, and its key similarities to and differences from the SERIOL model. Next I compare the mechanisms of positional gradient formation in the two models. After that I discuss the neural implementation of the SOLAR model's lexical matching algorithm, and the plausibility of this implementation. Then I discuss empirical attempts to adjudicate between the two models, focusing on the masked form priming paradigm, as well as the use of theoretical match values to test model predictions. The final section summarises the arguments and the evidence presented herein.

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AN OUTLINE OF LETTER POSITION CODING IN THE SOLAR MODEL

The SOLAR (Self-Organising Lexical Acquisition and Recognition) model was developed in order to explain how the visual word identification system is able to self-organise and operate in real-time in a realistic input environment (i.e., one that is complex, noisy, and continually changing). In the following I provide a brief schematic overview of the model's key assumptions, mechanisms, and processes. This description is necessarily relatively condensed, and focuses on those aspects of the model that are relevant to the subject of this paper, i.e., letter position coding. For a more detailed account of the model, including discussion of the model's capacity to self-organise and its novel lexical processing characteristics (such as its chunking behaviour and its mechanism for coding word frequency), the interested reader is referred to Davis (1999).

Visual word identification depends upon position-independent and context-independent letter units

The model assumes that fixation upon a letter string leads to the activation of letter detectors. The earliest stages of letter processing are assumed to activate letter representations that are case-specific and position-specific. However, word identification is assumed to depend upon the activation of abstract letter representations, abstract in the sense of being invariant representations that are not tied to a particular visual form or a particular visual location or serial position. The assumption of position-independent letter representations is one of the key features that distinguish the SOLAR model from previous models of visual word identification.

Spatial coding

In order to represent position across these position-independent letter units, the model makes use of an orthographic input coding scheme that I refer to as *spatial coding*. This scheme was inspired by the previous work of Grossberg (1978). The key idea is that serial order can be represented in terms of a dynamic activation pattern; this can be pictured as a distinct spatial pattern across letter nodes, hence the name spatial coding. In Davis (1999), I assumed that the spatial code was a primacy gradient of letter unit activities, and described how word detectors could learn to respond preferentially to specific spatial codes by self-organising their connections to letter units.

Formation of the spatial code via a serial scan

Another central assumption of the model is that this spatial code is formed by means of a serial process: a rapid left-to-right scan across letter representations that dynamically binds letter identity information with letter position information. This aspect of the model appears to have engendered some confusion (Whitney, 2008), which I seek to clear up in the section entitled The SERIOL Account of the Formation of the Positional Gradient.

Lexical matching

Another distinguishing feature of the model is the way in which the spatial code representing the visual input stimulus is compared to previously learned lexical representations. The assumption of a primacy gradient implies that standard dot-product coding matching mechanisms are inappropriate for spatial coding. If the dot-product were used, later letters would make a much smaller contribution to lexical matching than earlier letters, which is not plausible (indeed, it is likely that the final letter of a word plays a greater role in word identification than the immediately preceding letters). Instead, in the SOLAR model the input stimulus is compared to each learned representation (in parallel) by computing the difference between two spatial codes: one representing the input and one corresponding to the learned representation. The first of these spatial codes is reflected in the dynamic activities of the letter units; the second is coded in the weights that connect letter units to word detectors. These signal-weight differences can be represented as functions, with the width of the functions reflecting letter position uncertainty (see

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Figure 1). If the input stimulus represents a good match to the word coded by a given word detector, all of the signal-weight difference functions computed by that detector will be equivalent. This equivalence can be measured by computing the amplitude of the superposition of the relevant signal-weight difference functions. For example, Figure 1a depicts the match computations for the STOP word detector when the input stimulus is the matching word *stop*. As this represents a perfect match, the signal-weight difference functions are vertically aligned around a value of 0. This alignment gives rise to a

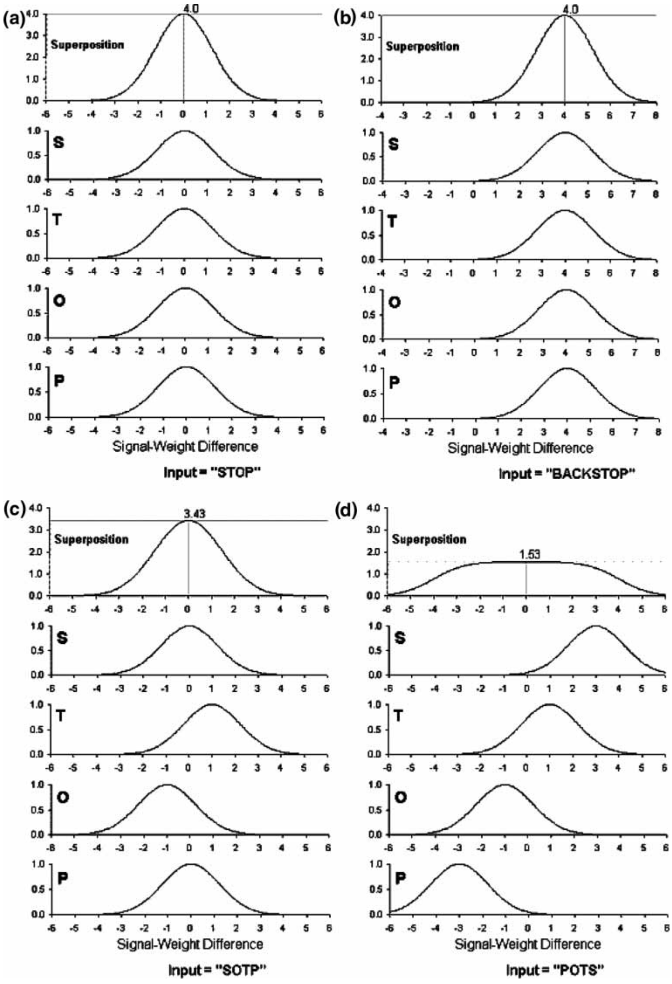

Figure 1. Signal-weight difference functions and superposition functions computed by the STOP word detector when the input stimulus is (a) *stop*, (b) *backstop*, (c) *sotp*, or (d) *pots*.

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superposition function (the top function) that has a relatively narrow distribution and a high amplitude. Full equations for computing the match value can be found in Davis (in press; see also Davis & Bowers, 2006).

Critically, it is the equivalence (harmony) of the signal-weight differences that is important, rather than their absolute value, and this aspect of the matching algorithm gives rise to position-invariant recognition. For example, Figure 1b depicts the match computations for the STOP word detector when the input stimulus is the letter string *backstop*. All of the signal-weight difference functions are centred on a value of 4 (because *stop* occurs four positions later in *backstop* than in the isolated word *stop*). This equivalence leads to a match value of 1, indicating that the word coded by this detector is present in the input. Good match values are also computed for close anagrams like *stop*-*sotp* (Figure 1c), although the match value is much smaller for distant anagrams, as in the case of reversed pairs like *stop*-*pots* (Figure 1d). Even though *stop* and *pots* are coded by exactly the same set of letter units, the spatial pattern of activities across these units is quite distinct, and hence the match value is relatively small (though nonzero, in contrast to open-bigram models; I return to this difference between the models in the penultimate section).

The basic spatial coding model has only a single parameter. This parameter, σ, represents the degree of letter position uncertainty. If very small values of σ are chosen (i.e., letter position coding is assumed to be extremely precise), the model cannot explain transposed-letter similarity effects; if very large values are chosen (i.e., letter position coding is assumed to be very coarse) the model has difficulty distinguishing even "extreme" anagrams like *balcony*-*bnoclay*. Intermediate values of this parameter are most plausible, and provide a good fit to empirical data concerning the relative similarity of different pairs (Davis, 2006, 2009).

Coding exterior letters

The basic spatial coding model treats all letter positions equally. However, this basic version of the model has difficulty accounting for evidence that the exterior letters of a word are accorded some special status. The assumption of end letter marking is one of a number of possible extensions to the model that can enable it to accommodate the special status of exterior letters (see Davis, in press, for further details). Specifically, it is assumed that the letter units that code the exterior letters of a letter string are (dynamically, and temporarily) assigned special markers, and these markers form part of the spatial code that is then matched against learned representations.

A good way for readers to understand how match calculations are computed in the SOLAR model is to experiment with the MatchCalc program.[1] This program also calculates match values for competing models, including the versions of the SERIOL model described by Whitney (2001, 2004).

Neural implementation of spatial coding and lexical matching

A possible neural realisation of the match computation is as follows (Davis, 2001). In the following, suppose that each letter "unit" corresponds to a population of neurons. Furthermore, suppose that the values of the spatial code are related to the phase at which the neurons within this population fire relative to an oscillating cycle. For example, suppose that when the input stimulus is *stop*, the spatial code of a primacy gradient across the letter units is transformed into a phase code in which the letter unit coding *S* fires first, followed by the *T*, the *O*, and finally the *P*. Suppose also that the weights connecting position-independent letter units to word detectors represent time constants, i.e., the time that it takes for a signal to be transmitted from the letter unit to the word detector, and that the pattern of these weights represents the learned spatial code. For example, the weights connecting letter units to the *STOP* word detector will be arranged such that the *S* takes longest to traverse, followed by the *T*, the *O*, and then the *P*. Consequently, each of these letter signals will arrive at the *STOP* word detector simultaneously (this synchrony is the realisation of the vertical alignment in Figure 1a). By contrast, when the input stimulus is *pots* the same letter units will fire, but their signals will arrive asynchronously at the *POST* detector (as depicted by the nonaligned signal-weight difference functions in Figure 1d). Thus, the superposition function in the mathematical description corresponds to the neural integration of temporally coincident signals.

Dissociated coding of identity and position information

Davis (1999) adopted the simplification that letter units were either active or inactive. In practice, however, many factors affect the perceptibility of letters, and it is desirable for this to be coded in continuous fashion by letter units. In the neural realisation proposed by Davis (2001) this is achieved by assuming that the degree of perceptual evidence supporting the presence of a particular letter affects the number of neurons that activate within the population corresponding to that letter. Thus, the mean amplitude of the population is an index of letter identity, with greater values for letters that are perceived more

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[1] The MatchCalculator program can be downloaded from http://www.pc.rhul.ac.uk/staff/c.davis/Utilities/MatchCalc/index.htm

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clearly. Note that this amplitude value is independent of the position of the letter, which is coded by the phase information, i.e., identity and position information are dissociated. This is not to say that letter position does not affect mean letter unit amplitude; in particular, external letters will tend to be coded by larger amplitudes than internal letters, because they suffer from less lateral masking (as discussed later). The addition of this letter identity information results in slight variations from the idealised situation depicted in Figure 1.

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SIMILARITIES AND DIFFERENCES BETWEEN THE SOLAR AND SERIOL MODELS

Similarities

Both models assume interhemispheric transfer. A common feature of the SOLAR and SERIOL models is the assumption that word identification processes are ordinarily lateralised to the dominant hemisphere. Thus, both models incorporate the assumption of interhemispheric transfer of letter identity information from the nondominant to the dominant hemisphere. For example, Davis (1999) discussed the possibility that the letter-by-letter reading observed in pure alexia may be in part a consequence of slow interhemispheric transfer. Hunter and Brysbaert (2008) have presented strong evidence for the role of interhemispheric transfer in visual word identification. It should be noted that the contention that interhemispheric transfer precedes word recognition proper is one that is implicitly shared by most current models. However, one exception is the model of Shillcock, Ellison, and Monaghan (2000), in which the information in the two hemispheres is integrated at a relatively late stage of the word identification process. Van der Haegen, Brysbaert, and Davis (2009) have recently reported experimental evidence challenging this account and supporting the account of the SERIOL and SOLAR models.

Both models assume a primacy gradient across letter units. Another point of similarity between the two models is that they both incorporate a level of processing that consists of abstract letter units that code position in terms of the relative activities of the different letters. Interestingly, Davis (1999) and Whitney (2001) independently arrived at the idea of a primacy gradient for coding letter position based upon different considerations.

In the case of the SOLAR model, the use of a primacy gradient was a direct response to the need to explain how position-independent letter units could represent position information. Some form of temporary, dynamic code seemed to be required, so that a letter unit that coded C in Position 1 of one letter string could subsequently code the letter C in Position 2 (or 3 or 4 or 5,

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etc.) of a different letter string. A monotonic positional gradient was a logical candidate solution, and this solution was made more attractive by the fact that much earlier work by Grossberg (1978) had argued that spatial patterns of activities are the fundamental unit of long-term memory for encoding sequences (see Page & Norris, 1998, for an example of how a similar coding scheme has been applied to serial order in short-term memory). Thus, the goal of achieving position-invariant recognition was a fundamental motivation in the development of spatial coding.

For Davis (1999), a further key source of empirical evidence against position-specific letter coding (and in favour of position-independent letter units) was provided by transposed letter (TL) similarity effects (i.e., the perceptual similarity of pairs like *trial* and *trail*; e.g., Andrews, 1996; Chambers, 1979; Forster, Davis, Schoknecht & Carter, 1987; O'Connor & Forster, 1981; Taft & van Graan, 1998). These effects provided a major motivation in the development of spatial coding, even though there was a limited empirical database at that time. In a comprehensive review of the extant data on TL similarity, Davis (1999) was able to note that "relatively few experiments have examined the effects of TL similarity on word recognition", but that the special case of TL pairs, "is important to study because it provides in many ways the most powerful model of the effects of orthographic similarity on visual word recognition. Furthermore, TL effects provide strong constraints on the nature of orthographic coding schemes" (pp. 311–312). Since that time there has been a rapid growth of interest in TL similarity effects, particularly in the masked priming paradigm (e.g., Frankish & Barnes, 2008; Guerrera & Forster, 2008; Lupker, Perea & Davis, 2008; Perea & Carreiras, 2006; Perea & Lupker, 2003a, 2003b, 2004; Schoonbaert & Grainger, 2004; van der Haegen et al., 2009), as well as in studies of reading (e.g., Johnson, Perea, & Rayner, 2007; Rayner, White, Johnson & Liversedge, 2006). The model described by Davis has been extremely successful in explaining these new data. The match computations depicted in Figure 1c illustrate the basis of TL similarity in the model: TL pairs activate exactly the same set of position-independent letter units, and position uncertainty implies that the signal-weight difference functions overlap even when letters are transposed.

None of the literature on TL similarity was cited in the original SERIOL paper (Whitney, 2001). Rather, the empirical database that provided the main motivation for the primacy gradient in the SERIOL model were the results from letter perceptibility experiments (e.g., Estes, Allmeyer, & Reder, 1976; Hammond & Green, 1982; Mason, 1982). This is perhaps slightly surprising, given that the typical empirical pattern observed in experiments investigating the perceptibility of centrally presented letter strings is not a primacy gradient, but, rather, a W-shaped function, i.e., performance is best for external letters and for the fixated letter (Averbach & Coriell, 1961; Mewhort & Campbell, 1978; Mewhort, Campbell, Marchetti, & Campbell, 1981; Stevens & Grainger, 2003). When letter strings are not directly fixated, but presented in the left visual field, right visual field, or bilaterally, there is an inverted U-shaped perceptibility function, i.e., the same exterior letter advantage (e.g., Butler & Currie, 1986; Lindell, Nicholls, Kwantes, & Castles, 2005; Townsend, Taylor, & Brown, 1971). Whitney (2001, 2008) seeks to explain the shapes of these functions with recourse to additional mechanisms; as discussed in the next section, the plausibility of these mechanisms is subject to question.

Both models incorporate a serial letter encoding mechanism. In the SOLAR model, the formation of a spatial orthographic code is attributed to a rapid left-to-right attentional scan across retinocentric (or possibly word-centred) letter detectors which enables position-independent letter units to be dynamically bound to a position code. Davis (1999) argued that orthographic input coding involved a rapid serial scan across letter detectors, and showed how this assumption could give rise to a primacy gradient across abstract letter units.

The serial encoding mechanism in the SERIOL model is a consequence, rather than a cause of the primacy gradient. According to this model, the primacy gradient results from a complex combination of facilitation and inhibition and a "gradient inversion" mechanism. This gradient induces a serial processing mechanism that activates sublexical units representing ordered letter pairs. In passing, I note that other models that posit the same type of sublexical representations do not find it necessary to invoke serial processing (e.g., Dehaene, Cohen, Sigman, & Vinckier, 2005; Grainger, Granier, Farioli, van Assche, & van Heuven, 2006). Thus, although both models incorporate a serial encoding mechanism, the function and locus of this mechanism differs in important respects across the models.

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Differences

Whitney (2008) lists three "core differences" that distinguish the SERIOL and SOLAR models. These are: (a) the role of serial processing, (b) the nature of the highest prelexical representation, and (c) the lexical activation functions. Although there are other importance differences between the models (such as the ability of the SOLAR model to self-organise its own lexical representations), in respect to the issue of letter position coding, I fully concur with Whitney's list. One important qualification that needs to be made, however, concerns, the nature of the highest prelexical representation in the SOLAR model.

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Sublexical units in the SOLAR model. In the SOLAR model, word units can be activated directly by letter units, and this is the mechanism for lexical activation that has been the focus of recent tests of the model. However, it is important to note that the model also predicts the emergence of sublexical units. These sublexical units are represented at the same level of coding as lexical units, and it was for this reason that Davis (1999) eschewed the nomenclature of "the letter level", "the word level", etc., preferring to refer to a hierarchy of orthographic coding levels $O^{(1)}$, $O^{(2)}$, etc., where $O^{(2)}$ represents recurring letter sequences, including both words and sublexical units. There are two main factors that are likely to lead to the acquisition of sublexical units. The first of these is the recurrence of a unit—in particular, its recurrence in contexts where it represents a component of the input pattern that is not "explained" by other chunks. For example, suppose that the words *walk*, *talk*, and *play* have been unitised, and the model is now exposed to the novel inputs *walking*, *talking*, and *playing*. In each of these inputs the identification of the familiar chunks (*walk*, *talk*, and *play*) leaves the recurring component -*ing*. Over time, this will lead to the unitisation of this component. The representation of such morphemic units offers the possibility of explaining masked morphological priming data (e.g., Forster et al., 1987; Grainger, Colé, & Segui, 1991; McCormick, Rastle, & Davis, 2008), as well as other empirical data that point to prelexical decomposition of morphologically complex stimuli (e.g., Burani & Caramazza, 1987; New, Brysbaert, Segui, Ferrand, & Rastle, 2004; Taft & Forster, 1975). The second main factor influencing unitisation is the association of a letter sequence with a consistent semantic and/or phonological pattern. Once again, the example of the affix -*ing* is relevant: This affix is typically associated with a particular semantic/syntactic concept (the progressive tense of a verb) and a specific pronunciation, resulting in relatively consistent feedback that supports the unitisation of this affix. Likewise, particular word bodies may be consistently associated with particular phonological rimes (e.g., the body of *alk* is usually pronounced as in *talk*, *walk*, etc.), and this may support the acquisition of these sublexical units. Thus, the SOLAR model predicts that letter sequences such as bound morphemes and consistent word bodies are particularly likely to be unitised. Letter sequences that are likely to be unitised are those that have some intrinsic "adaptive value"—those that are likely to occur and that can provide useful evidence concerning the meaning or pronunciation of letter strings.

Sublexical units in the SERIOL model. The sublexical units posited in the SERIOL model are ordered letter pairs (Grainger & van Heuven, 2003, coined the term "open bigrams" to describe these units). In contrast to the sublexical units envisaged in the SOLAR model, the SERIOL model's assumption of open bigram units is entirely independent of factors such as statistical recurrence and consistent semantic and/or phonological associations. For example, open bigrams that correspond to particularly likely letter combinations are not more likely to be represented in the model. All possible open bigrams must be represented in the model in order for it to be able to represent letter strings successfully. Likewise, open bigrams are not associated with consistent semantics or phonology. For example the CT open bigram that is activated in words like *act*, *cat*, *city*, and *chat* is clearly not a useful source of information consisting the meaning of the stimulus, nor is it a particularly helpful guide to its pronunciation (no better than the individual letter units that are assumed to activate open bigrams). A similar argument against open bigram units has been made recently by Goswami and Ziegler (2006).

The SOLAR and SERIOL models differ with regards to their explanatory scope. Whitney (2008) notes that, "At the lexical level, the SERIOL specification is actually much simpler than SOLAR" (p. 173). Indeed, this is a critical difference between the models. Although the SERIOL model provides a detailed account of the processes involved in establishing a letter position code, it does not attempt to provide a detailed account of lexical processing. The SOLAR model, by contrast, attempts to provide a quite detailed account of the processes underlying lexical activation and selection. The match values computed by word detectors provide the bottom-up input to a competitive process that is based on lateral inhibition between word detectors. The model implements differential equations that are integrated over time, enabling it to make specific predictions concerning response latency in tasks such as lexical decision, and to simulate critical data, notably masked form priming effects. The ability to explicitly model behavioural findings is extremely valuable, as it can otherwise be difficult to evaluate the implications of such findings for models of orthographic input coding. As noted later, the restricted scope of the SERIOL model makes it difficult for the model to explain various critical data, and raises some problems with respect to the generation of experimental predictions.

In summary, there are several points of similarity across the SERIOL and SOLAR models. Both models assume that visual word recognition necessitates the activation of abstract, position-independent letter units in the dominant hemisphere, which requires initial interhemispheric transfer of letter identity information from the nondominant hemisphere. However, although both models assume a positional gradient across letter units, the mechanism for achieving this gradient and the original theoretical motivation for positing such a gradient differs between the models. Likewise, although both models incorporate a serial encoding process, the function of this process is a key difference between the models. The SERIOL model assumes that lexical representations receive inputs from open bigram units via a dot product matching algorithm, whereas the SOLAR model assumes that lexical representations can be activated directly by position-independent letter units

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by means of a lexical matching algorithm that computes signal-weight differences. Finally, the SOLAR model embodies explicit hypotheses about lexical activation processes, whereas the SERIOL model does not offer a detailed account of lexical processing. These differences are discussed in greater detail later.

THE SERIOL ACCOUNT OF THE FORMATION OF THE POSITIONAL GRADIENT

As noted, the SERIOL and SOLAR models both assume a monotonic positional gradient across position-independent letter units, but the two models offer quite different accounts of how this gradient is formed. I consider the SERIOL account in this section, and the SOLAR account in the next section.

Whitney (2001) describes a number of novel mechanisms for transforming a symmetrical, inverted V-shaped acuity gradient into a monotonically descending activation gradient. This transformation requires three assumptions. First, features in the left visual field are assumed to be coded by larger activities than those in the right visual field. Second, it is assumed that there are strong directional lateral inhibitory connections in the right (but not the left) hemisphere. The resulting interactions are assumed to have the effect of inverting the activity gradient in this hemisphere (such that a monotonically increasing gradient is transformed into a monotonically decreasing gradient). Finally, feature information is transferred from the right hemisphere to the left hemisphere, effectively concatenating two monotonically decreasing gradients. The first assumption (concerning the difference between the left and right visual fields) ensures that the resulting concatenation is itself a monotonically decreasing gradient.

Whitney (2001) cites data from experiments on the perceptibility of letter and symbol strings as evidence for the above processing assumptions. A key datum is the initial letter advantage that is standardly observed in experiments in which participants are asked to report letters from letter strings that are presented very briefly (e.g., Averbach & Coriell, 1961; Butler & Currie, 1986; Lindell et al., 2005; Mewhort & Campbell, 1978; Mewhort et al., 1981; Stevens & Grainger, 2003; Townsend et al., 1971). A conventional explanation of the superior report of the initial letter attributes this phenomenon to lateral masking: The first letter is subjected to less lateral masking than the interior letters of a string (e.g., Bouma, 1970; Chung, Levi, & Legge, 2001). Whitney (2001, 2008) rejects this explanation on the basis that an initial symbol advantage is not observed when the critical stimuli are briefly presented symbol strings (e.g., Hammond & Green, 1982; Mason, 1982; Tydgat & Grainger, 2009). Instead, symbol strings show a serial position function that reflect a visual acuity gradient, i.e., there is faster and more accurate identification for symbols closer to fixation, with accuracy lowest for exterior symbols. Whitney (2001) concluded that there is a specialised system for analysing alphanumeric strings, and that it is this system that gives rise to the initial letter advantage.

However, there are a number of problems with this account, and, more generally, with the SERIOL model's account of gradient formation. First, it is not clear that the model succeeds in explaining the perceptibility data that Whitney (2001) cites in support of this account. If the monotonic gradient has been established by the level of feature representations in V4, it is not clear why this would not also produce an initial-symbol advantage for symbol arrays. This explanation seems to require that the features used to code symbols, such as the Greek letters used by Mason (1982), are entirely nonoverlapping with those used to code alphabetic letters and digits. Furthermore, the SERIOL model's account of gradient formation cannot explain the advantage that is commonly reported for final letters, relative to immediately preceding letters.[2] Whitney (2001) invokes a separate, later mechanism to explain this final letter advantage (the continued firing of the node that codes the final letter of the string until the end of the oscillatory cycle), but her summary of letter perceptibility data tends to exclude final letters (see for example, Whitney, 2001, Fig. 4). Nor does the monotonic gradient explain the advantage for the central letter relative to immediately adjacent letters (based on the SERIOL account, one would expect the central letter to be identified less well than the letter to its left). A more parsimonious explanation of the W-shaped accuracy function for briefly presented letter strings is offered by the combination of an acuity gradient and lateral masking. Tydgat and Grainger (2009) describe how such a model can also explain the pattern observed for symbol strings.

An even more serious problem with the SERIOL account is its fundamental incompatibility with lateral masking. It is not just that the model *can* explain phenomena such as the initial letter advantage without invoking lateral masking as an explanatory mechanism. Rather, the model is committed to the claim that lateral masking does *not* affect the featural representation. The model's primacy gradient formation mechanism requires that the activation of letter features follows a symmetrical, inverted U-shaped acuity gradient, i.e., that the features of the letter in the initial

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[2] The final letter advantage has been reported in both the bar probe task (e.g., Averbach & Coriell, 1961; Mewhort & Campbell, 1978; Mewhort et al., 1981; Tydgat & Grainger, 2009) and in target search (e.g., Mason, 1982). However, recent research suggests that the final letter advantage in target search varies as a function of positional letter frequency (Pitchford, Ledgeway, & Masterson, 2008) as well as varying across languages, as evidenced by different patterns for Greek and English (Ktori & Pitchford, 2008). As Pitchford et al. (2008) note, the latter findings may reflect top-down contributions from lexical processes.

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position of a centrally presented word are perceived less well than those of the letter in the second position, and the features of the final letter are perceived less well than those of the penultimate letter. If lateral masking did disrupt the pattern imposed by the acuity gradient (e.g., by favouring exterior letters), the SERIOL's model account of gradient formation would fail; for example, the final letter would be coded by a larger activity than the penultimate letter, leading to order confusions. This aspect of the model's account is rather problematic, in view of the fact that lateral masking (also known as crowding) phenomena are pervasive in visual perception (see Levi, 2008, for a recent review). It might be possible to incorporate additional mechanisms to compensate for the effects of lateral masking, but this would not rectify the deeper problem, which is the model's confounding of letter perceptibility with letter position information. The model's invocation of hemispheric asymmetries and gradient inversion mechanisms aims to translate a hypothesised pattern of letter activation into an ordered letter string. In general, though, it is not possible to guarantee that there is a consistent relationship between how well a letter is perceived and its position in a string. This relationship will vary depending upon factors such as fixation position and stimulus quality. It does not seem plausible to suggest that manipulations that affect letter perceptibility will disrupt coding of letter position (e.g., that dimming the central letters will cause them to be perceived as occurring later than the final letters), but this counterintuitive prediction is exactly what is implied by the SERIOL account. In summary, the SERIOL model's account of the formation of the positional gradient is complex and unparsimonious, depends upon neural mechanisms that have no independent support, does not offer a satisfactory account of letter (or symbol) perceptibility data, is fundamentally incompatible with basic aspects of visual perception, and leads to implausible predictions regarding the relationship between letter perceptibility and letter position coding.

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THE SOLAR ACCOUNT OF THE FORMATION OF THE POSITIONAL GRADIENT

The orthographic input level of the SOLAR model is a working memory field that transforms serial sequences into spatial patterns. Davis (1999) used working memory equations developed by Grossberg and colleagues (Bradski, Carpenter, & Grossberg, 1992; Grossberg, 1978; cf. Page & Norris, 1998) to achieve this transformation. A similar result might be achieved by some other mechanism that assigned a phase code on the basis of the order of arrival of letters. The critical idea is that the model dynamically assigns a position code to position-independent letter units by means of a rapid sequential scan across the letters of the stimulus.

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Davis (1999) suggested that a simple way to implement a rapid serial readout of this sort is to make use of a type of neural network architecture known as an *avalanche network* (Grossberg, 1969; cf. Houghton's, 1990, *competitive queuing* model for a very similar architecture). In this type of network, serial readout is achieved by means of simple facilitatory and inhibitory interactions. Figure 2 illustrates the basic mechanism. The top of the figure depicts a set of position-independent letter units. These units receive excitatory inputs from corresponding position-specific letter units (the preceding level of the network, e.g., a position-independent *A* unit can receives inputs from position-specific units coding *A* in Position 1, *A* in Position 2, etc.). At the bottom of the figure, there is a node labelled "Scan!" that is assumed to be automatically activated by letter strings (e.g., when there is activity in letter detectors). This node is connected to a network consisting of a set of "readout" nodes. Each of the latter nodes is connected to one set of position-specific letter nodes, i.e., to a particular letter channel. These connections are bidirectional: The readout node sends strong excitatory signals to the corresponding letter channel, which in turn send a strong inhibitory signal back to the readout node. There are also inhibitory connections between the readout nodes. Thus, when a readout node fires, it activates its corresponding letter channel, causing the most active letter node (or nodes, i.e., those above some threshold) in this channel to fire and send excitatory signals to the position-independent letter level. This activation is brief, however, because the strong inhibition that the readout node receives from its channel causes it to switch off. This in turn shuts off its inhibitory signal to other readout nodes, allowing a new readout node to fire. Consequently, when the "Scan!" node fires the readout network will activate a sequence of letter channels in an order that is determined by the relative

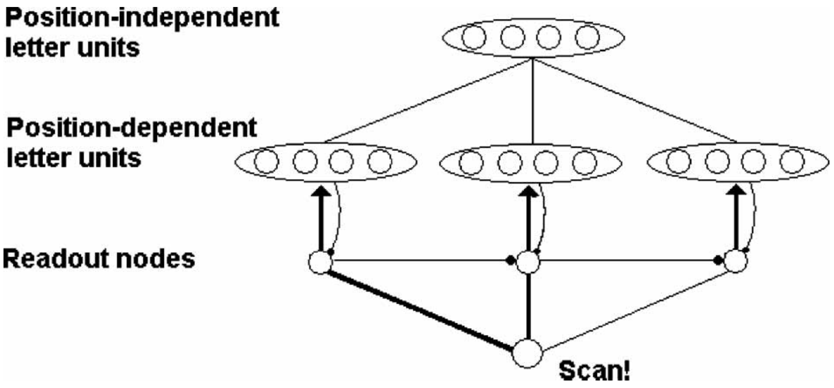

Figure 2. An avalanche network for performing a serial "scan" of position-specific letter units. Lines terminating with filled-in circles are inhibitory connections. See text for details.

strength of the inputs to each of the readout nodes. In the figure, the weights to the readout network decrease from left to right. This is assumed to be the consequence of learning to read a left-to-right language; if the reader learnt to read a language that was right-to-left the sequence of weights would be reversed (i.e., would decrease from right to left), and thus a readout signal would result in letters being read from right to left.

One implication of this model of gradient formation is that letters are assigned positions according to their relative order in the sequential scan, rather than according to their physical position. It follows that manipulations that maintain relative order while varying physical position (within reason) should not influence letter position coding. Masked form priming experiments reported by Grainger and colleagues (Grainger et al., 2006; Peressotti & Grainger, 1999; see also Humphreys, Evett, & Quinlan, 1990) support this account. Thus, a six-letter target is primed equally effectively by four-letter primes in which Letters 2 and 5 are simply deleted (1346 primes, e.g., *grdn*-GARDEN) as by primes in which these letters are replaced by "-" symbols (e.g., *g-rd-n*-GARDEN). Although such data have been claimed to be problematic for the SOLAR model (Whitney, 2008), the equivalence of 1-34-6 and 1346 primes is a natural prediction of this model.

There are a couple of potential confusions concerning the terms "serial scan" and "serial readout" that merit clarification. The first of these concerns exactly what operation it is that is being performed in serial. It might erroneously be imagined that serial readout implies that the constituent letters of the stimulus are identified serially, left-to-right. However, Davis (1999) emphasised that letter identification occurs in parallel in the model. That is, in Figure 2, nodes in each of the letter channels start to activate simultaneously. The serial process in the model relates to the communication between these position-dependent letter units and the position-independent letter units that form the orthographic input level.

A second potential confusion of the terms "serial scan" and "serial readout" is that they imply a slow, volitional process. The description of the SOLAR model in Whitney (2008), in which the serial readout process is depicted as slow, effortful, and attention demanding, illustrates this confusion. However, Davis (1999) emphasised that the hypothesised serial scan was an extremely rapid process. In discussing the transition from beginning to skilled reading, I commented that, "the serial component becomes increasingly rapid, so that it approaches a parallel process. If the inputs to $O^{(1)}$ arrive sequentially, but in extremely rapid succession, then the distinction between serial and parallel input becomes somewhat blurred" (p. 87). In summarising data that might be relevant to determining the speed of the serial process, I wrote, "I have attempted to argue for a distinct serial hypothesis in which the input rate is approximately 10–20 ms per letter" (p. 99).

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In summary, the SOLAR model embodies very different assumptions about the formation of the positional gradient from those in the SERIOL model. Position is assigned at the level of letters, rather than at the level of features, and depends upon a serial readout, rather than upon mechanisms that convert letter perceptibility into letter position. Indeed, letter perceptibility is entirely orthogonal to letter position information in the SOLAR model. The mechanism used to achieve this serial readout can be specified at the level of basic neural network circuits that have been used to explain serial encoding in short-term memory as well as in other domains of perception. Although this requires a serial process, it is assumed that this process is very rapid in skilled readers. If the automatic readout network has been damaged it may become necessary to rely on an effortful scan—this may provide a possible explanation of processing in letter-by-letter reading. Ordinarily, however, the process is so rapid as to be virtually indistinguishable from a parallel process. Indeed, the speed with which the scan ordinarily operates in skilled reading may be one of the factors that gives rise to letter position uncertainty.

THE NEURAL PLAUSIBILITY OF THE SOLAR MODEL'S LEXICAL MATCHING ALGORITHM

The SOLAR model's algorithm for lexical matching—computing the bottom-up match between the input stimulus and a previously learned code—is discussed in detail in Davis (in press). In the present section my aim is to consider the neural plausibility of this algorithm, given that this plausibility has been challenged in a recent critique of the model (Whitney, 2008).

The proposed neural instantiation of the SOLAR model's matching algorithm entails three components: (a) the transformation of a primacy gradient into a temporal phase code, (b) the notion of temporal coincidence detection, and (c) the subtraction of weights from signal strengths. I argue that each of these components of the model is neurally plausible.

Recent neurophysiological studies on visual cortex have directly observed that the phase in the gamma cycle at which pyramidal neurons fire depends on their activation strength (Nikolic, Haeusler, Singer, & Maass, 2007; Schneider, Havenith, & Nikolic, 2006). This is exactly the kind of mechanism that would be required to transform a primacy gradient into a temporal phase code, e.g., such that the first letter of the stimulus is coded by neurons that fire earlier within an oscillating cycle than the second letter, and so on. It is also relevant to note that place information (i.e., a rat's position within its environment) has been shown to be coded by the phase with which pyramidal cells in hippocampus fire relative to the theta cycle (e.g., Harris et al., 2002; Mehta, Lee, & Wilson, 2002). It does not seem too far-fetched to draw a parallel between the use of phase information to code one's own physical position with the possibility of using phase to code the position of objects within the environment, including letters within a word. It is interesting to note that evidence is emerging that the theta cycle may play an important role in visual word identification; for example, measurements of the theta cycle during reading distinguish normal readers from those with developmental dyslexia (Klimesch et al., 2001; Spironelli, Penolazzi, Vio, & Angrilli, 2006).

The idea that neurons function as temporal coincidence detectors has a long history (e.g., Abeles, 1982; Braitenberg, 1967; Jeffress, 1948; Licklider, 1951; Olsen & Suga, 1991). There are now a very large number of physiological studies that suggest that postsynaptic neurons are more likely to fire in response to synchronous presynaptic inputs (i.e., the temporal window over which neuron integrate their inputs is quite small). In recent times, the question appears to have changed from "Can neurons function as coincidence detectors?" to "Is coincident input *necessary* to generate action potentials?" Thus, temporal coincidence detection appears to be a highly plausible neural mechanism for implementing the theoretical idea of a superposition of signal-weight difference functions.

An aspect of the SOLAR model's calculations that has been somewhat contentious (Whitney, 2008) is the computation of signal-weight differences. Within the neural implementation that has been outlined, the purpose of this computation is to allow word detectors to "decode" the temporal code set up across letter units, so that the input signals arrive at the word detector in synchrony (thereby allowing the match with the stored word to be computed on the basis of the temporal coincidence of the incoming signals). This decoding requires shifting the phase of incoming letter signals; that is, weight subtraction corresponds to phase shifting. How could this phase shifting be implemented in the brain?

The simplest possibility is that the weights connecting letter units to word detectors correspond to axonal delays, that is, the greater the value assigned to the weight, the longer it takes for the signal to be conducted from the letter unit to the word detector (note that these weights are not multiplicative as in simple dot-product models). In this way, letters that occur earlier in the word are coded by larger activities, and hence fire earlier in the cycle, but take longer to reach the detector for the corresponding word. Thus, signals from all of the constituent letters will be temporally coincident at a word detector with a set of axonal delays that matches the spatial code corresponding to the stimulus. The idea of using delay lines in a neural network model goes back 60 years, to Jeffress (1948). In an influential paper, he proposed that a system of delay lines connecting inputs from the two ears with temporal coincidence detectors could be used to localise auditory signals. Rather impressively, neurophysiological studies on birds and mammals have shown that this theoretical model is essentially

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correct (e.g., Carr & Konishi, 1988; Yin & Chan, 1990). Shackleton, Skottun, Arnott, & Palmer (2003) recorded from cells in the inferior colliculus of guinea pigs that function as temporal coincidence detectors, and found that individual cells are sufficiently sensitive to interaural time difference to accomplish sound localisation at the level of psychophysical performance. Joris (2006) noted that the delay line model introduced by Jeffress (1948) and generalised by Licklider (1951), now "forms the basis for virtually all computational models of binaural hearing" (p. 969).

Furthermore, temporal delay models are not restricted to the auditory modality. The most well-known example of such mechanisms in the visual domain are Reichardt detectors (Reichardt, 1961). These are motion detectors that are tuned to a certain speed and direction of motion because of the pattern of delay lines by which they are connected to visual receptors. In order for a simple Reichardt detector to receive temporally coincident signals (and hence fire) the visual receptors must fire in the correct sequence, with the appropriate delay between signals. This type of circuit is closely analogous to the circuits connecting word detectors and letter units in the SOLAR model. Physiological and psychophysical studies indicate that motion vision in flies is based on Reichardt detectors (e.g., Haag, Denk, & Borst, 2004), and the same general principles are applicable to human vision (van Santen & Sperling, 1985).

Although I have often cited delay lines as a means of phase shifting (e.g., Davis, 2001, 2004), it is not necessary to assume that the specialised delay line circuits found in the auditory brain stem are also found in other parts of cortex. There are many conceivable neural mechanisms that achieve exactly the same functional outcome. For example, other possibilities that have been canvassed include inhibitory postsynaptic potentials of varying duration (e.g., Olsen & Suga, 1991) and various biochemical time constants such as calcium concentration (e.g., Fiala, Grossberg, & Bullock, 1996). Given that precise timing is a requirement of many aspects of perception and action, we can be quite confident that the cortex has the necessary mechanisms to implement the temporal delays that are posited in the model.

In summary, each of the key steps required for the lexical matching computations posited by the SOLAR model can be implemented through neurally plausible mechanisms. Direct physiological evidence has been observed for phase coding, temporal delay, and temporal coincidence detection. Although the model is essentially a functional model, and does not aim to provide a detailed account of processing at the level of individual neurons, there is no reason to believe that such an account could not be provided by researchers with the necessary expertise.

INITIAL ATTEMPTS TO ADJUDICATE BETWEEN THE SOLAR AND SERIOL MODELS

An initial attempt to use experimental data to adjudicate between the SOLAR and SERIOL models was reported by Davis and Bowers (2006), who compared the relative perceptual similarity of substitution neighbours (SNs) and neighbours once removed (N1Rs). The latter form of similarity refers to orthographic neighbours that combine a letter substitution and a transposition, as in *stop* and *soap*. This comparison was of great theoretical interest because, among the five models of letter position coding under consideration by Davis and Bowers (2006), only one—the SOLAR model—predicted that SNs like *stop* and *shop* are more similar than N1Rs like *stop* and *soap*. The open bigrams shared by *stop* and *shop* are identical to those shared by *stop* and *soap*: This reflects the fact that open bigrams activate both for contiguous and noncontiguous letter pairs. Thus, in a discrete open bigram coding model (as described by Schoonbaert & Grainger, 2004), in which open bigrams are either active or inactive, the match values associated with SNs and N1Rs are identical. The original SERIOL model (Whitney, 2001) predicts that *stop* and *soap* are *more* similar than *stop* and *shop* (the match values are .57 and .49 respectively). This prediction was tested in three separate experiments, and in each case the SERIOL prediction was falsified and the SOLAR prediction was confirmed. In addition, two other specific predictions of the SERIOL model were shown to be incorrect. First, the model predicted that letter substitutions at Position 4 of a five-letter word would result in a considerably closer match with the original word than letter substitutions at Position 2 (the match values are .79 and .54 respectively). Similarly, the model predicted that $N1R_4$ primes that replace the fourth letter of the target (e.g., *anxke*-*ANKLE*; match = .76), should be more similar to the target word than $N1R_2$ primes that replace the second letter of the target (e.g., *akxle*-*ANKLE*; match = .62). In neither case did the empirical priming data show any difference between these conditions.

The reason that the original SERIOL model made these incorrect predictions is related to a fundamental characteristic of its letter position coding: The activities of open bigrams in the model confound letter position and letter contiguity. As Davis and Bowers (2006) noted,

> A bigram's activity can be smaller than 1 either because it is noncontiguous, or because its initial letter occurs in a medial position, or both: the recipient word node has no way to distinguish amongst these possibilities. Similarly, a bigram's activity can be close to 1 either because it is the initial contiguous bigram of a letter string, or because it is the open-bigram formed by the combination of the initial letter and the final letter (i.e., the "least" contiguous, but the most perceptible). It is this confound between the two types of information coded by bigram activities that

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> causes the SERIOL model to make a prediction in the opposite direction to the data. While it is desirable to code the effects of serial position on a letter's perceptibility, problems of this sort indicate the necessity of disentangling this factor from letter contiguity. (p. 550)

The unconfounding of letter position and letter contiguity at the open bigram level (though not the letter level) has been implemented in the current version of the SERIOL model (Whitney, 2004).[3] This modification to the model allows it to make the correct predictions regarding the effects of letter replacements at different letter positions (i.e., that position of replacement does not matter, at least for internal positions) and the relative perceptual similarity of SNs and N1Rs for five letter words. The model still makes an incorrect prediction for four-letter words, and so the relative similarity of SN and N1R pairs continues to pose a problem with the model.[4]

Whitney (2008) argues that the fact that the modified SERIOL model is consistent with (most of) this data implies that the underlying theory of Whitney (2001) was not invalidated. There is a metatheoretical issue here concerning the distinction between models and simulations, and whether models can be falsified. A different perspective on model testing was advanced by Davis (1999), who argued that simulations of falsifiable models are critical for the development of a unified theory. As Lewandowsky (1993) notes, "simulations of unified theories are not written to implement a model; rather, the model is the simulation" (p. 241). Nevertheless, the key point for present purposes is that the SOLAR model made a prediction regarding the relative similarity of these pairs which was unique to that model, and the data reported by Davis and Bowers (2006) therefore falsified the four competing approaches that they considered, including the original SERIOL model of Whitney (2001). This revealed a critical flaw in that model, which has subsequently been corrected in a revised version of the model. Likewise, the discrete open bigram model discussed by Schoonbaert and Grainger (2004) has been superseded by the overlap open bigram model of Grainger et al. (2006), in which open bigrams have continuous activities that reflect the degree of letter contiguity. Thus, the empirical program that has been driven by predictions of the

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[3] The experiment of Davis and Bowers (2006, which was originally reported at a symposium of the ESCoP conference in 2003) was designed to test the model described by Whitney (2001); we did not become aware of the revised SERIOL model described in Whitney (2004; i.e., Whitney's unpublished PhD dissertation) until 2006.

[4] Whitney (2008) suggests that this result could be captured by changing the parameters of the SERIOL model. However, the parameter modification that she proposes has the unintended consequence of making nonadjacent transposition neighbours like *casino* and *caniso* considerably more similar, and thereby leaves the model unable to explain another finding: the larger priming effects for one-letter different primes (e.g., *cavino-CASINO*) than for non-adjacent transposition primes (e.g., *caniso-CASINO*). This result was originally reported by Perea and Lupker (2004) in Spanish and was subsequently replicated in English, as reported by Davis and Bowers (2005).

SOLAR model has accelerated the theoretical progress not only of this model, but also of other competing models.

BEYOND MATCH VALUES

The model predictions discussed in the previous section were based entirely on match values, with the underlying assumption being that priming effects should be driven by the magnitude of the orthographic match between the prime and the target. However, this assumption is a simplification: Match values do not map directly onto priming effects. The importance of avoiding this confusion has been highlighted by computational modellers in recent discussions of the relationship between match values and masked priming effects (e.g., Davis, 2003, in press; Lupker & Davis, 2009; van Heuven & Grainger, 2007). Masked priming effects are not simply a function of prime–target overlap (as measured by match values), but also of the prime's similarity to lexical competitors of the target.[5]

The most extreme case of lexical competitor effects occurs when the prime is itself a word, in which case priming effects are often inhibitory (e.g., Davis & Lupker, 2006; de Moor & Brysbaert, 2000; Segui & Grainger, 1990). For example, Davis and Lupker (2006) found that responses to a target word like SNORT were facilitated by neighbour primes that were nonwords (e.g., *snolt*-SNORT), but that the same target words were inhibited by neighbour primes that were themselves words (e.g., *short*-SNORT). Note that in this example the lexical competition effect causes the priming effect to change its direction from facilitatory to inhibitory, despite the fact that the exact same match value is computed for *snolt*-SNORT and *short*-SNORT (e.g., the SERIOL match value would be .66 in both cases). That is, the match value alone is insufficient to predict the direction of priming effects, let alone their magnitude. Making accurate predictions in such cases requires a fully implemented model of word identification that takes match values as the input to a competitive process of lexical selection. To this end, Davis and Lupker (2006) showed that simulations of a modified interaction activation model (McClelland & Rumelhart, 1981) could provide a good fit to their data. The restricted scope of the SERIOL model, by contrast, prevents it from modelling such prime lexicality effects.

In the case where the prime is not a close match to the target, even relatively distant lexical competitors can exert a strong influence on masked form priming effects. In a recent paper, Lupker and Davis (2009) argue that such

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[5] This point is not intended to invalidate the data discussed in the previous section. The stimuli in Davis and Bowers (2006) were carefully designed to control lexical competitors across the SN and N1R conditions, as described in the Method section of Experiment 2.

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lexical competitor effects explain the absence of priming effects for the "extreme" transposition primes studied by Guerrera and Forster (2008). For example, Guerrera and Forster studied a type of form prime that they referred to as T-All ("transposed all") primes, in which each successive pair of letters in the target is transposed (e.g., *avacitno*-*VACATION*). Their results showed that T-All primes did not produce any priming relative to all-letter different control primes, a finding that they argued was problematic for all current models of letter position coding, including the SERIOL and SOLAR models. This conclusion was challenged by Lupker and Davis (2009), who argued that the reason that the T-All prime *avacitno* is not an effective prime for the target *VACATION* is not that there is no orthographic similarity between the codes for these two letter strings, but rather that *avacitno* is *more* similar to words like *AVIATION*, which compete with the target word during the identification process. This argument was supported by a simulation of an interactive-activation model in which the original position-specific coding scheme was replaced by a spatial coding scheme. The reason for using a modified interactive-activation model in this simulation was to facilitate comparison with the previous simulations reported by Davis (2003) and Davis and Lupker (2006); nevertheless, the SOLAR model is part of the same family of competitive network models as the interactive-activation model, and it makes equivalent predictions for the form priming experiments considered here. Lupker and Davis's (2009) simulation showed that the modified interactive-activation model correctly predicted the absence of priming for T-All primes, and inspection of the model demonstrated that this was because of the influence of lexical competitors.

In addition to explaining why match values do not map directly onto priming effects in the standard masked priming paradigm, simulations of a fully implemented model of word identification offer an insight into how to modify the standard methodology so as to make observed priming effects a more sensitive measure of the match between the prime and the target. The basis of this modified methodology, called sandwich priming, is that lexical competitor effects can be overcome if the activation of the target node is given an initial headstart. This can be achieved by preceding the prime of interest (i.e., either a related form prime or an unrelated control prime) with a brief (masked) presentation of the target word. Lupker and Davis (2009) have recently demonstrated that this technique enables large and statistically robust form priming effects to be obtained for primes that show no priming when the conventional masked priming technique is used. For example, Lupker and Davis replicated Guerrera and Forster's (2008) finding of no priming for T-All primes, but also showed that exactly the same stimuli produced a 40 ms priming effect when the sandwich priming technique was used. Simulations show an excellent fit to these data, i.e., no T-All priming in conventional priming but large priming effects in sandwich priming. By contrast, the

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SERIOL model has no mechanism for explaining the difference between conventional and sandwich priming.

Another task that shows great promise for overcoming lexical competitor effects, and thereby providing more sensitive tests of models of letter position coding, is the cross-case same-different task that has recently been revived by Norris and Kinoshita (2008; Kinoshita & Norris, 2009). In this task, participants are asked to determine whether an upper case target string is identical to a previously presented lower case reference string. Norris and Kinoshita (2008) showed that large priming effects are obtained in this task, and that priming is obtained for both word and nonword targets, suggesting that the locus of priming is prelexical. Recent experiments in my laboratory have shown that extreme transposition primes such as T-All primes result in significant priming in this task. This result provides converging evidence for Lupker and Davis's (2009) argument about the interpretation of null priming effects in the conventional (lexical decision) masked priming methodology.

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The above discussion of match values is also relevant to considering an experiment proposed by Whitney (2008) for the purpose of adjudicating between the SOLAR and SERIOL models. A critical difference between the two models concerns the relative similarity of reversed letter strings. An extreme example can be seen in the case of fully reversed pairs like *stop* and *pots*: The SOLAR model predicts a small amount of overlap (see Figure 1d), whereas the SERIOL model predicts no overlap at all. This is because the string reversal has the effect of completely disrupting the ordered letter pairs within the target. Although pairs like 1234-4321 test the limits of open-bigram coding, it is desirable to consider stimulus pairs that are matched with respect to their first and last letters, given the potential importance of exterior letters (and the fact that both models incorporate mechanisms for coding the exterior letters). Whitney (2008) suggests that priming from reversed interior strings of the form 1654327 (e.g., *pimaryd*-PYRAMID) should be compared with priming from subset strings of the form 1237 (e.g., *pyrd*-PYRAMID). The SERIOL match for 1237 is greater than the match for 1654327, whereas the reverse is true for the SOLAR model. In the case of 1654327, the match value is .62 for the SOLAR model, versus only .20 for the SERIOL model. Whitney (2008) uses this pattern of match values to make a prediction about masked priming effects: "[T]he prime 1654327 must provide at *least as much* facilitation as 1237 under SOLAR. In contrast, SERIOL predicts that 1654327 should provide significantly less facilitation than 1237" (p. 177).

The foregoing discussion makes it clear that predictions based purely on match values must be treated with caution. In order to generate a prediction for the SOLAR model it is necessary to go beyond the computation of match values and perform a simulation of the model when these primes and targets are processed. In fact, the model predicts that (using the standard priming methodology), 1237 primes are more effective than the 1654327 primes.

Indeed, no priming is found for the latter condition, as the result of lexical competitor effects (e.g., the prime *pimaryd* activates the lexical competitor *primary* more strongly than the target *pyramid*). This further suggests that sandwich priming should increase the likelihood of priming being observed for 1654327 primes, and simulations of the implemented model predict that the 1654327 condition should be effective when sandwich priming is used.

In conclusion, then, despite the limitations of predictions based purely on match values, the development of more sensitive priming methodologies means that it is possible to adjudicate between models of letter position coding. Although the SOLAR model and the revised SERIOL model make many similar predictions concerning orthographic similarity, they continue to differ with respect to their underlying principles, and so it is possible to generate predictions that differentiate the models. The investigation of the similarity of letter strings that comprise the same letters in reverse order offers a promising approach to adjudicating between the letter position coding schemes of the SOLAR and SERIOL models, because it enables a test of a fundamental claim of the SERIOL model, i.e., that lexical representations are activated by ordered letter pairs.

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CONCLUSION

The SOLAR model has inspired a substantial programme of empirical research, both by the present author in collaboration by others (e.g., Bowers, Davis, & Hanley, 2005a, 2005b; Davis & Bowers, 2004, 2006; Davis & Lupker, 2006; Davis, Perea, & Acha, 2009; Davis & Taft, 2005; Lupker & Davis, 2009; Perry, Lupker, & Davis, 2008), as well as by other researchers who have tested the model's predictions (e.g., Andrews, Miller, & Rayner, 2004; Brunsdon, Coltheart, & Nickels, 2005; Guerrera & Forster, 2008; Johnson et al., 2007; Kinoshita & Norris, 2009; Perea & Carreiras, 2006; Perea & Fraga, 2006; Perea & Lupker, 2003a, 2003b, 2004; Schoonbaert & Grainger, 2004; van Assche & Grainger, 2006; Welvaert, Farioli, & Grainger, 2008). The underlying assumptions of the model have sometimes been misunderstood (e.g., Mariol, Jacques, Schelstraete, & Rossion, 2008; Rastle & Davis, 2008), and certain aspects of the model have recently been criticised (Whitney, 2008). I have sought to address some of these confusions and criticisms in the present paper by providing an overview of the spatial coding and match calculations assumed in the model, and a defence of the neural plausibility of these assumptions. I have also directly compared the SOLAR model with the SERIOL model. Although there are some points of similarity between these two models, there are key differences with respect to the nature (and function) of the serial encoding mechanisms in the two models, as well as their orthographic input coding schemes. These differences lead the models to make different predictions, and where these predictions have been tested, they have favoured the SOLAR account. The SERIOL model, on the other hand, is lacking in neural plausibility, is incompatible with basic perceptual constraints, and is unable to accommodate critical orthographic similarity data. Overcoming these problems will necessitate radical revisions to the fundamental assumptions of the model.

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