28

Isn't that *Fantabulous*? How Similarity Motivates Intentional Morphological Blends in English

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1 Introduction

Blending is a productive word-formation process which involves coining a new word out of two source words. Some English examples are listed in (1); parenthesized letters are omitted from the blend and underlined letters are present in both source words.

(1) a. br(eakfast) □ (l)unch → brunch
    b. m<u>ot</u>(or) □ (h)<u>ot</u>el → m<u>ot</u>el
    c. foo<u>l</u> □ (phi)<u>l</u>osopher → foo<u>l</u>osopher
    d. au<u>ster</u>(e) □ <u>stern</u> → au<u>ster</u>n
    e. alco<u>hol</u> □ <u>hol</u>iday → alco<u>hol</u>iday

As is obvious, blending comes in several closely related types: (1a) is an instance where the two source words do not overlap in the resulting blend; (1b), by contrast, involves two overlapping letters, viz. <ot>. (1c) and (1d), then, are cases where either the first or the second source word respectively are entirely present in the blend, and (1e) is a case where both source words are entirely present in the blend. While it is difficult to for-

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mulate a definition of blends that neatly distinguishes between blends and other subtractive word-formation processes (cf. López Rúa 2002), for the present paper I will adopt the following, probably uncontroversial, definition of blending: Blending is the intentional coinage of a new word by fusing parts of at least two source words. Usually, at least, the fore part of the first source word (sw_1) is combined with the hind part of the second source word (sw_2) and there is some phonemic or graphemic overlap of the source words.

While blending is reasonably productive, the mechanisms governing it have largely remained opaque: Most studies on blending are mainly taxonomic in nature (cf., e.g., Pound (1914), Algeo (1977), Cannon (1986), Štekauer (1991)) and contribute little to the explanation of why blends have the structure they have. Notable exceptions to this tendency are recent studies by Kubozono (1990), Lehrer (1996), Berg (1998), Kelly (1998), Kaunisto (2000) and Gries (2004, to appear). One determinant of blend structure that is mentioned in most of these studies is that blends often play with (i) the similarity of the source words to each other and (ii) the similarity of the source words to the blend;[1] of course, these kinds of similarity are related to the recognizability of the source words (but cf. Section 3).

Lehrer (1996: 366) hypothesized that '[t]he more material from the target word that is present, the easier the blend is to identify'.[2] This claim is problematic since it would predict one of the following two findings: either we should not have many blends in the first place (since the coinage of a blend usually involves shortening and thus threatens the degree of recognizability of the source words), or blends should on average be quite long since, when the blend coiner wants his blend to be recognized, he would tend to use much of the source words in the blend. This, however, is not what we find: many blends are rather short, running the risk of damaging the recognizability of the source words: *brunch* (*breakfast* □ *lunch*), *bit* (*binary* □ *unit*), *amping* (*amphetamine* □ *smoking*), to name just a few examples. Therefore, similarity involves more than just leaving the source words largely untouched. Also, the empirical evidence adduced by Lehrer is not truly supportive since the total correlations she reports do not exceed the rather meager value of .21 (without any significance values).

Kaunisto (2000) is also concerned with the degree of recognizability of

[1] These two kinds of similarity need not be identical. Consider, e.g., *skittenish* (*skittish* □ *kittenish*), where the two kinds of similarity are virtually identical: The source words are very similar both to each other and to the blend, but if the two words had been blended into the theoretically possible, though practically unlikely, *sish*, the two source words would of course still be very similar to each other, but they would be much less similar to the much shorter blend. Thus, to be on the safe side, these two kinds of similarity must be distinguished.

[2] One might argue whether this is not in fact the null hypothesis holding for all words.

the source words, claiming that '[i]deal blends then would naturally be ones where the ending of the first source word and the beginning of the second one overlap, resulting in a way in no deletion at all'. He goes on to argue that, since the deletion of x letters will be more detrimental to the identification of shorter source words, shorter source words should contribute relatively more material to blends than longer source words. His hypothesis is superior to that of Lehrer since it does not merely imply long blends, but predicts a probabilistic interaction of source word lengths and contributions. The empirical evidence Kaunisto presents seems to support his hypothesis, but is also fraught with problems. First, it is based on a fairly small corpus (101 blends); second, it is not subjected to standard tests of significance; finally, neither does it distinguish between phonemic and graphemic contributions nor between different ways to analyze the amount of material contributed by source words to blends. For example, the blend *chunnel* can be analyzed in the two ways represented in (2), but only the first analysis supports Kaunisto's hypothesis. In the light of these drawbacks, Kaunisto's hypothesis needs to be tested somewhat more rigorously.

(2) a. ch(annel) □ (t)unnel → chunnel (analysis$_1$)
b. ch(a)<u>nnel</u> □ (t)u<u>nnel</u> → chunnel (analysis$_2$)

Finally, Kelly (1998: 586-8) has mentioned similarity in connection with the playful character of blends. However, his operationalization of word play via similarity is too narrow since it is reduced to the similarity of consonants at the breakpoint (e.g. the similarity of [t] and [d] in *clandestine* and *fantastical*) although it is obvious that these words are much more similar to each other in that both share the articulatory features or even segments given in (3) and are stressed on their second syllable.

(3) consonant (cluster) | [æ] | [n] | [alveolar plosive] | [frontal unrounded] | [s] | [t] | [□ | [consonant]

A broader perspective on similarity would therefore incorporate various levels at which similarity is operative. Given this complexity of an at first glance deceptively simple notion of similarity, how exactly similarity should be operationalized is of course a nontrivial issue. For example, according to Kemmer (2003: 75-6),

> [s]imilarity can range from segmental identity through segmental similarity to same or similar syllable structure; and the similarity can range from identity/similarity of the blend with both source lexemes, to one source lexeme, or to parts of these.

Section 2 of this paper discusses empirical evidence on how different kinds of similarity influence blend formation on different linguistic levels. Section 2.1 will begin by studying the role similarity plays for blend formation by examining the hypothesis put forward by Lehrer and Kaunisto. Section 2.2 will investigate the similarity of source words to each other while Section 2.3 addresses the similarity between source words and their blends.

2 Case Studies

2.1 Degree of Recognizability

In order to test the predicted interaction between the source words' lengths and contributions, 988 blends in my corpus were coded according to which source word is longer and which source word contributes more of its elements to the blend (according to both ways of analysis exemplified in (2) and both in the written and spoken medium, i.e. counting letters and phonemes). The result is summarized in Table 1.[3]

which word is longer?	which word contributes more to the blend?			total
	=	sw_1	sw_2	
=	160	104	244	508
sw_1	172	154 (-)	916 (+)	1,242
sw_2	408	1,278 (+)	516 (-)	2,202
total	740	1,536	1,676	3,952

Table 1. Length □ contribution of source words

A loglinear analysis reveals that the predicted interaction (circled in Table 1) is in fact significant; pluses/minuses in parentheses indicate that the observed frequencies are highly significantly higher/lower than expected. Kaunisto's prediction receives strong support: shorter source words indeed contribute more of themselves to blends across both ways of analysis and media.[4] This finding receives additional support from two sources. Neither an analogous analysis of the phonemic contributions of source words to authentic speech error blends nor an analogous analysis of the contributions of source words to (228 graphemic and 146 phonemic) simulated blends

[3] Not all analyses in this section are based on exactly the same corpus data since (i) for some blends different coding possibilities are available and (ii) for some other blends, different native speakers produce different results (e.g. stress patterns). Every case study below only investigates the blends with unanimous judgments.

[4] Space does not permit an exhaustive discussion of all significant effects of the loglinear analysis; cf. Gries (2004) for more detailed discussion (on the basis of a smaller corpus).

yielded any such significant effects.[5] In sum, blend formation is indeed governed by a desire to ensure the recognizability of the source words.

2.2 The Similarity of the Source Words to Each Other

This section will investigate the degree to which the similarity between source words plays a role for the formation of blends. This issue has so far mainly been investigated for speech-error blends (cf., e.g. MacKay 1987: 34), but since speech error blends are sometimes considered similar in nature to intentional blends (cf. Berg 1998: 152, 156), it might be expected to also hold for intentional blends. Also, the claim that source words of intentional blends are similar to each other is implicit in all the studies relating blends to the notion of word play. This section will clarify to which degree the findings concerning error blends carry over to intentional blends (cf. also Gries to appear). First, however, we need an operationalization of the similarity of two words; two strategies are pursued here. Section 2.2.1 investigates similarity on the level of phonemes and graphemes while Section 2.2.2 examines similarity on the phonological level, looking at syllabic lengths and stress patterns.

2.2.1 Phonemic and Orthographic Similarity

A widely-used measure of word form similarity is the Dice coefficient and one of its derivatives, namely XDice (cf., e.g., Brew and McKelvie 1996; for a similar measure, cf. Vitz and Winkler 1973). The Dice coefficient measures the similarity of two words by dividing the number of bigrams (of letters) that two words share by the number of all their bigrams; (X)Dice ranges from 1 (identity) to 0 (complete dissimilarity). Consider, for example, the bigrams of the source words of *chunnel*, namely *channel* and *tunnel*: *ch*, *ha*, *an*, *nn*, *ne*, *el* and *tu*, *un*, *nn*, *ne*, *el*. Obviously, the two words share the six underlined bigrams (out of eleven), resulting in a Dice value of 6÷11=.545. The corresponding XDice value results from also including bigrams that arise when the second letter of a *tri*gram is omitted: *ca*, *hn*, *an*, *ne*, *nl* and *tn*, *un*, *ne*, *nl*. Correspondingly, XDice is now (6+4)÷(11+9)=.5.

These computations were performed for the above 988 blends. Before

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[5] The simulated blends were created as follows: Six pairs of words were randomly chosen such that each relation of source word lengths ($sw_1=sw_2$, $sw_1>sw_2$, $sw_1<sw_2$) is represented by two pairs of source words; the words of each pair belonged to the same word class. Then I coined all possible blends out of each pair of words. Consider, e.g., the graphemic blends of the words *strong* and *powerful*. I started with *strong* as sw_1 and attached successively smaller parts of *powerful* to it, resulting in *strongowerful*, *strongwerful*, *strongerful* etc. up to *strongl*. Then, *strong* was shortened by one letter to *stron*, to which *powerful* and again successively shorter parts of *powerful* were added. This process stopped after the shortest possible blend of *strong* and *powerful*, namely *sul*. Doing this for all six word pairs resulted in 228 graphemic and 146 phonemic blends, the length frequencies of which were approximately normally distributed.

we can turn to the results, however, two further steps need to be taken. First, as in Sections 1 and 2.1 above, we need to distinguish orthographic and phonological properties of blends. Accordingly, I also computed (X)Dice on the basis of phonemes for the 988 blends. The pronunciation of the source words was extracted from the CELEX database; words whose pronunciation were not listed there were checked in the Collins Cobuild Dictionary.

The second necessary step was to identify the base level against which the Dice and XDice coefficients of the source words should be compared. It would be futile to compare the (X)Dice values of the blends' source words against an average (X)Dice value of zero since most words are similar to each other to at least some degree. Therefore, I assembled a corpus of 1,000 random word pairs (noun-noun pairs, verb-verb pairs and adjective-adjective pairs in proportions matching the average blend word class frequencies reported by Kubozono 1990: 3). Then the spellings and phonemic transcription of the 2,000 words were extracted from the CELEX database to compute Dice and XDice for each of the 1,000 word pairs. The weighted means of the (X)Dice coefficients as influenced by the medium (graphemes vs. phonemes) and source word type (authentic intentional blend vs. random words) were then analyzed with a MANOVA (cf. Table 2); the expectation was that source words of blends should exhibit a higher degree of similarity than randomly assembled word pairs.

	grapheme	phoneme	overall mean	
source words of intentional blends	.144	.146	.145	Dice
	.141	.131	.136	XDice
random word pairs	.055	.028	.041	Dice
	.062	.026	.044	XDice
overall mean	.099	.087	.093	Dice
	.101	.078	.09	XDice

Table 2. Source word type □ medium and their influence on Dice/XDice

First, there is the predicted effect of the source word type: source words of intentional blends exhibit more similarity to each other than randomly chosen words ($F_{2,\ 3971}$=275.54; partial $□^2$=.122; p<.001). Second, blends exhibit more graphemic than phonemic similarity ($F_{2,\ 3971}$=29.96; partial $□^2$=.015; p<.001) but the effect size is rather small. Finally, there is an interaction of source word type and medium ($F_{2,\ 3971}$=5.41; partial $□^2$=.003; p=.005), but this interaction has only a minimal effect size.

Words that are intentionally blended exhibit a much higher degree of phonemic and graphemic similarity to each other than might be expected by chance. This effect strongly supports the assumption derived from MacKay's (1987) findings on speech-error blends and Berg's (1998) conclusion that speech-error blends and intentional blends exhibit some similarities.

2.2.2 Phonological Similarity

A natural extension of examining the phonemic and orthographic similarity of the source words to each other would be to also inspect (i) the syllabic lengths of source words, and (ii) the stress patterns of the source words.

As to (i), assuming that similarity governs the choice of source words, one would expect to often find identical source word lengths. Thus in Table 3, summarizing the distribution of syllabic lengths of 1,028 blends, the highest frequencies should be within the italicized main diagonal.

length sw_1	length sw_2						total
	1	2	3	4	5	6	
1	*56*	105	126	49	11	□	347
2	49	*91*	101	55	6	3	305
3	38	65	*77*	50	11	1	242
4	12	26	37	*31*	2	2	110
5	2	3	9	7	*1*		22
6	1		1				2
total	158	290	351	192	31	6	1,028

Table 3. Syllabic length source word$_1$ □ syllabic length source word$_2$

While the overall sw_1 lengths approximately follow a Zipfian distribution, sw_2 exhibits a strong tendency to be either two or three words long. In fact, for each length of sw_1, trisyllabic sw_2's are most frequent. This constitutes counterevidence to the above expectation so that, with respect to this criterion, the role of similarity must be considered disproven.

As to (ii), on the assumption that source words tend to be similar, one would expect the stress patterns of equally long source words of blends to be identical.[6] To test this expectation empirically, I determined all stress patterns of the source words and crosstabulated all blends according to the stress patterns of source words nested within source word lengths. Table 4 represents the result for source word lengths with up to four syllables (given

[6] Recall that we are currently only concerned with the similarity between source words *irrespective of how they are blended*—from the latter perspective, identically-stressed source words can be difficult since blends consisting of the fore part of sw_1 and the hind part of sw_2 would then pose the problem of where to assign stress (as in *hurricane* □ *tycoon* → *hurricoon* or *survey* □ *review* → *surview*).

the rarity of blends with longer source words documented in Table 3).

For the circled subtables, χ^2-tests were computed testing whether the observed distributions differed significantly from those expected from the overall frequencies of stress patterns. More precisely, the expectation for the 2+3+4=9 main diagonal cells in the three subtables was that their (italicized) frequencies should be the highest within their respective rows and columns. This prediction was borne out in six of the nine cases (those in bold type); for example, in the 3×3 table, 32 is higher than 15 and 2 as well as 5 and 3. While the 2×2 table did not reach statistical significance, the 3×3 and the 4×4 tables did,[7] and there is no significant effect in the opposite direction; I consider this evidence supporting the role of similarity.

sw_2 / sw_1		1	2		3			4			
		S	Su	uS	Suu	uSu	uuS	Suuu	uSuu	uuSu	uuuS
1	S	56	82	22	76	41	9	9	22	18	-
2	Su	43	***63***	15	45	34	8	11	8	26	1
	uS	6	9	*4*	8	5	1	-	3	5	1
3	Suu	28	41	6	***32***	15	2	3	9	17	1
	uSu	7	15	1	5	***17***	3	4	6	7	-
	uuS	3	1	-	3	-	-	-	-	2	-
4	Suuu	2	7	3	4	1	-	***6***	2	2	-
	uSuu	3	7	2	8	7	1	-	***4***	2	1
	uuSu	7	6	1	8	8	-	2	2	***9***	-
	uuuS	-	-	-	-	-	-	-	1	-	-

Table 4. Stress pattern source word$_1$ × stress pattern source word$_2$ (S=stressed syllable; u=unstressed syllable)

2.3 The Similarity of the Source Words to the Blend

The previous section demonstrated that source words of blends are similar to each other. However, we also need to look at whether source words are also similar to the resulting blends or, put differently, whether source words are blended in a way that results in a high similarity to the blend; cf. above n. 1. Although this assumption seems to be tacitly taken for granted, the number of empirical tests of this assumption is again rather small. In this connection, the operationalization is even more complicated since not only do we have to compare two source words to each other, but the joint simi-

[7] The χ^2-test (a goodness-of-fit between partial and complete table) for the 2×2 table was insignificant ($\chi^2(1)$=.97; p>.32); the test for the 3×3 table was very significant ($\chi^2(4)$=18.31; p≈.001); the test for the 4×4 table was highly significant ($\chi^2(9)$=28.74; p<.001).

larity of two source words to a third item, namely the blend. Again, two approaches will be taken: by analogy to the structure of Section 2.2, Section 2.3.1 investigates the phonemic/orthographic similarity of source words to blends while Section 2.3.2 examines the phonological similarity between source words and blends.

2.3.1 Phonemic and Orthographic Similarity

To perform an adequate empirical test of something as complex as similarity, in earlier work (cf. Gries 2004, to appear) I devised a similarity index for graphemes and phonemes (henceforth SI_G and SI_P respectively). By analogy to Tversky's (1977) contrast model, where similarity increases/decreases with increasing/decreasing numbers of shared features, SI_G and SI_P are based on the proportion of graphemes (or phonemes) each source word contributes to the blend according to analysis$_2$ *together with* the proportion these graphemes/phonemes make up in the blend. For (*channel* □ *tunnel* →) *chunnel*, where we would intuitively expect a high value, SI_G is computed as follows: *chunnel* consists of seven graphemes, six of which are contributed by the seven-letter word *channel* and five of which are contributed by the six-letter word *tunnel*. That is to say, 85.7% (6 letters out of 7) of *channel* make up 85.7% (6 letters out of 7) of *chunnel*, and 83.3% (5 letters out of 6) of *tunnel* make up 71.4% (5 letters out of 7) of *chunnel*, resulting in (4).

(4) $$SI_{G\,(chunnel)} = \frac{\left(\frac{6}{7} \cdot \frac{6}{7}\right) + \left(\frac{5}{6} \cdot \frac{5}{7}\right)}{2} = \frac{.735 + .595}{2} \;\square\; .665$$

This index can, of course, not be interpreted on the basis of a single raw value, but comparing it to a case where we would intuitively expect a much lower value, e.g. *brunch*, already demonstrates the validity of this measure: *brunch* does indeed result in a much lower SI_G value, namely .304.

As can be inferred from (4), SI_G and SI_P are devised such that their theoretical upper bound is 1 (representing the extreme case of similarity, viz. identity) whereas their theoretical lower bound is 0 (representing the extreme case of absolute dissimilarity). However, simply computing average SI_G and SI_P values for 988 intentional blends is not sufficient since we again need a baseline against which these average values can be compared: as in Section 2.2.1, the null hypotheses would not simply be that SI_G and SI_P equal zero since most words X and Y are similar to each other to at least some degree (cf. also Kelly 1998: 587), which would obviously manifest itself in a blend coined out of X and Y. Thus, as baseline SI_G/SI_P values, I computed the mean SI_G/SI_P values for the simulated blends created independently for the validation of the recognizability hypothesis in Section 2.1.

If similarity does indeed govern the formation of blends, we would expect that the formation of authentic intentional blends should result in higher SI_G/SI_P values than the formation of simulated blends. The weighted means resulting from a subsequent ANOVA are represented in Table 5.

	mean SI_G	mean SI_P	overall mean
intentional blends	.503	.508	.506
simulated blends	.365	.352	.358
overall mean	.477	.488	.482

Table 5. Blend type × Medium and their influence on similarity

The ANOVA reveals that the source words of intentional blends are much more similar to their blends than the source words of the simulated blends ($F_{1,\ 2346}$=403.4; partial η^2=.147; p<.001) whereas the medium as well as the interaction of blend type and medium are not significant ($F_{1,\ 2346}$<1; partial η^2<.001 and $F_{1,\ 2346}$=1.6; partial η^2<.001; p=.206 respectively). Less technically, the results show that source words of authentic blends are blended in such a way that the blends still exhibit a strong similarity to the original source words. By contrast, if words are merely arbitrarily blended in all phonologically possible ways, then the degree of similarity between source words and blends decreases strongly. This finding demonstrates that Kelly's case study was basically on the right track, but the present results are a necessary extension since they underscore the importance of a much more global understanding of similarity.[8] The next section will now be concerned with the phonological similarity of source words to blends.

2.3.2 Phonological Similarity

Let us now also investigate the similarity of source words to the blend in phonological terms by returning to some potentially relevant factors (already examined in Section 2.2 above), namely (i) the syllabic lengths of the source words and (ii) the stress pattern of the source words of blends.

As to the first factor, Kubozono (1990: 15) reported what he called the length rule: the length of the blend corresponds at least to the length of sw_2 in 78.2% of all 142 cases, but much less frequently at least to the length of sw_1 (only 22.5%).[9] However, Kubozono does not explain why the length

[8] Note in this connection that *brunch* is similarity-wise not an ideal blend: its SI_G value is even below the average of completely arbitrarily blended words, and for some reason the similarity-wise better blend *breakfunch* ($SI_{G\ (breakfunch)}$=.36) has not been chosen at the time of creation.

[9] Here *at least* means that the two sets denoted by the percentages may overlap because of the blends which are as long as both source words; this also explains why 78.2+22.5>100%.

rule should exist.[10] Neither does he report any standard results of significance nor can these be computed on the basis of the data he reports, which is why his result, especially given the limited size of his corpus, must be taken with a grain of salt. Coding 1,011 intentional blends for these variables yielded the results represented in Table 6 (for ease of comparison reported in a format similar to Kubozono's; the expected frequencies were computed from all configurations of individual word lengths).

relation between sw_1, sw_2 and the blend	observed		expected
sw_1 = blend ≠ sw_2 (e.g. *gas* □ *alcohol* → *gasohol*)	145 (14.3%)	=	144 (14.2%)
sw_1 = sw_2 = blend (e.g. *terrible* □ *horrible* → *torrible*)	151 (14.9%)	>	56 (5.5%)
sw_1 ≠ sw_2 = blend (e.g. *guess* □ *estimate* → *guesstimate*)	431 (42.6%)	>	192 (19%)
sw_1 = sw_2 ≠ blend (e.g. *cinema* □ *musical* → *cinemusical*)	101 (10%)	<	183 (18.1%)
sw_1 ≠ sw_2 ≠ blend (e.g. *dense* □ *nylon* → *densylon*)	183 (18.1%)	<	436 (43.1%)

Table 6. Relations between syllabic lengths of source words and blends

Kubozono's findings can be clearly replicated and receive statistically significant support ($\chi^2(4)=642.24$; $p<.001$). While the present percentages differ somewhat from those of Kubozono's smaller corpus, there is still an obvious and significant tendency to blend source words such that the length of the blend corresponds to that of sw_2 (57.5%), something we much less frequently observe for sw_1 (only 29.3%). Finally, cases where the blend has a length different from at least one source word are conspicuously less frequent than expected (cf. the last two rows of Table 6). That is, as in Section 2.1, sw_2 is on average privileged in determining the blend's final shape.

Let us now turn to the second factor, the stress patterns of source words and blends. In the same way that sw_2 seems to (probabilistically) determine the blend's length (rather than sw_1), it also seems to determine the blend's stress pattern (Quirk et al. 1985: 1583). As before, however, the empirical

[10] Kubozono (1990: 16) suggests that the length rule implies that sw_2 is the head of the blend, but provides little evidence for this claim: his discussion of the semantic constraints on blending (p. 3-4) does not distinguish between error blends and intentional blends and the 'righthand head rule' Kubozono refers to is not universally confirmed as he himself points out (p. 17).

support for this assumption is rather modest, which may be due to the fact that few blend corpora are large enough for the required crosstabulations. To some extent, this is also true of the present corpus, the size of which was decreased by the fact that native speakers often disagree as to how a blend is pronounced (cf. above n. 3, 6); this case study is therefore based on only 614 blends (with up to four syllables).

To measure the correlation between the stress patterns of source words and blends, I crosstabulated all stress patterns of source words (as in Table 4 above) with those of the blends, obtaining the results listed in Table 7.

relation between sw_1, sw_2 and the blend	observed		expected
sw_1 = blend ≠ sw_2 (e.g. *playboy* □ *bore* → *playbore*)	84 (13.7%)	≈	70 (11.4%)
sw_1 = sw_2 = blend (e.g. *soldiers* □ *rebels* → *sobels*)	129 (21%)	>>	18 (3%)
sw_1 ≠ sw_2 = blend (e.g. *mirth* □ *earthquake* → *mirth-quake*)	337 (54.9%)	>	80 (13%)
sw_1 = sw_2 ≠ blend (e.g. *river* □ *landscape* → *riverscape*)	10 (1.6%)	<<	99 (16.1%)
sw_1 ≠ sw_2 ≠ blend (e.g. *gallop* □ *parade* → *gallopade*)	54 (8.8%)	<<	347 (56.5%)

Table 7. Relations between stress patterns of source words and blends

This distribution is again statistically highly significant (□^{2}(4)=1817.87; p<.001), strongly supporting previous work: sw_2 is in fact dominant in determining the blend's stress pattern (cf. rows 2 and 3). However, in more general terms the influence of similarity is even more pronounced. First, the greatest difference is observed for cases where the source words and the blend are equally stressed, which happens seven times as frequently as expected in spite of the potential difficulties of stress assignment (cf. above n. 7). Second, there is a strong tendency for the blend to have the stress pattern of at least one source word: cases where both source words and the blend exhibit different stress patterns are much less frequent than might be expected by chance (cf. the last row). Thus similarity does play a role in determining a blend's stress pattern.

3 Conclusion

The analyses in Sections 2.1 to 2.3 are among the first to provide empirical evidence on the role of similarity for intentional blend formation and illustrate that similarity is important for two temporally different but related stages of blend formation. First, Section 2.2 showed that the blend coiner apparently chooses to blend source words (i) that denote the semantic concepts required for the blend to have its intended effect and (ii) that are similar to each other in terms of letters, phonemes, and stress patterns—the only exception to this pattern is that sw_2 tends to be trisyllabic irrespective of the length of sw_1 (I must admit to having no explanation for this preference).

Secondly, according to the results of Sections 2.1 and 2.3, the blend coiner blends the identified source words in such a way that (i) the source words are still recognizable and (ii) the resulting blend is still sufficiently similar to both source words in terms of letters, phonemes, length, and stress pattern. It is interesting to note, though, that the degree of recognizability of the source words interacts with the desire to maximize similarity. The degree of recognizability would require putting as much of the source words into the blends as possible (cf. Lehrer 1996). On the basis of letters and phonemes, *clandestinantastical* is easier to recognize as a blend of *clandestine* and *fantastical* than, say, *clastical*, but *clandestinantastical* is not very similar to the source words anymore: it is much longer than either source word, it does not make use of the possibility of highlighting the source words' similarity by overlapping, and it does not preserve the stress pattern of either source word. Similarity, on the other hand, would require (i) that the blended source words are similar to each other and (ii) that the source words are blended in a way that increases overlap and preserves lengths and stress patterns: *clandestical* and *clantastical* (the authentic blend) involve the deletion of more material than *clandestinantastical*, but are coined such that the blend is similar to both source words (which is why their similarity indices are among the highest possible ones, ranked 9 and 4 respectively).

On the one hand, this suggests that the similarity-motivated preservation of one source word's stress pattern was considered more important than the recognizability-motivated preservation of letters and phonemes. On the other hand, the dominance of sw_2 noted above underscores the relevance of recognizability: Since the part of sw_2 entering into the blend is not its beginning (which would facilitate its recognition most; cf. Noteboom 1981) but its end, it is only logical to put more of sw_2 into the blend to facilitate its recognition in spite of its unnatural presentation. It is interactions like these which point to the need for further analyses of blends in order to shed light on how different conflicting cues for blend-formation are resolved, and which information-processing strategies speakers utilize in this connection.

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