A close call: Interference from semantic neighbourhood density and similarity in language production

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Abstract

The present study investigated how lexical selection is influenced by the number of semantically related representations (semantic neighbourhood density) and their similarity (semantic distance) to the target in a speeded picture-naming task. Semantic neighbourhood density and similarity as continuous variables were used to assess lexical selection for which competitive and noncompetitive mechanisms have been proposed. Previous studies found mixed effects of semantic neighbourhood variables, leaving this issue unresolved. Here, we demonstrate interference of semantic neighbourhood similarity with less accurate naming responses and a higher likelihood of producing semantic errors and omissions over accurate responses for words with semantically more similar (closer) neighbours. No main effect of semantic neighbourhood density and no interaction between semantic neighbourhood density and similarity was found. We assessed further whether semantic neighbourhood density can affect naming performance if semantic neighbours exceed a certain degree of semantic similarity. Semantic similarity between the target and each neighbour was used to split semantic neighbourhood density into two different density variables: The number of semantically close neighbours versus distant neighbours. The results showed a significant effect of close, but not of distant, semantic neighbourhood density: Naming pictures of targets with more close semantic neighbours led to longer naming latencies, less accurate responses, and a higher likelihood for the production of semantic errors and omissions over accurate responses. The results show that word inherent semantic attributes such as semantic neighbourhood similarity and the number of coactivated close semantic neighbours modulate lexical selection supporting theories of competitive lexical processing.

Keywords Language production · Semantic processing · Lexical selection · Semantic neighbours

The aim of the present study was to test theories of lexical selection using semantic neighbourhood variables in speeded picture naming. Lexical selection is one of the core steps in language production that determines whether the lexical representation of a target word is successfully selected amongst other simultaneously activated, semantically related representations

(also referred to as semantic neighbours). Problems with lexical selection are one of the most common reasons for word-finding difficulties in acquired language impairments, such as stroke aphasia, which often lead to the inability to produce correctly intended words. Potential treatments depend on a thorough understanding of the nature of lexical selection and on the variables that affect its ease or difficulty (e.g., spoken word frequency, semantic typicality, age of acquisition). Previous research suggests that word-finding difficulties in individuals with acquired language impairments may be caused by unresolved interference from semantic neighbours (e.g., Ellis, 1985; Stemmer, 1985; Wheeldon & Monsell, 1994). However, to date, only a few studies have investigated the effects of semantic neighbourhood on word production, and the reported findings are heterogeneous across studies.

Language production theories generally agree that when a speaker intends to produce a word, the meaning is activated at the conceptual (semantic) level and forwarded to the word's representation at the lexical level. During this process, semantic activation not only spreads to the target but also to

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representations that share some of the target's meaning—the semantic neighbours. Hence, activation of semantic neighbours has its origin at the conceptual level and results in the coactivation of related representations at the lexical level. What remains debated is how the target is selected amongst its semantic neighbours, and, specifically, whether the number and semantic similarity of semantic neighbours interferes with the target's lexical selection.

According to noncompetitive theories of lexical selection (Dell, 1986; Dell, Schwartz, Martin, Saffran, & Gagnon, 1997; Finkbeiner & Caramazza, 2006; Mahon, Costa, Peterson, Vargas, & Caramazza, 2007; Morton, 1985; Oppenheim, Dell, & Schwartz, 2010), semantic neighbours do not compete and thus do not interfere with lexical selection. Instead, lexical selection is proposed to be determined by a target's activation strength alone, whereby a lexical representation has to reach a certain level of activation (Dell, 1986; Dell et al., 1997) or threshold in order to be selected (e.g., Miozzo & Caramazza, 2003; Morton, 1969, 1985).

Competitive theories (e.g., Levelt, Roelofs, & Meyer, 1999; Roelofs, 1992, 2018; Wheeldon & Monsell, 1994) assume that lexical selection of a target word is strongly influenced by its semantic neighbours. In order to be selected, the lexical representation of a target has to overcome interference from its coactivated semantic neighbours. Competition can be implemented in different ways. For example, Levelt et al. (1999) proposed a selection mechanism based on the Luce choice rule (e.g., Luce, 1959; Roelofs, 1992) whereby the probability of a target word's selection depends on its own level of activation divided by the summed activation of its semantic neighbours. Other models assume lateral inhibition between semantic neighbours at the lexical level (e.g., Cutting & Ferreira, 1999; Harley, 1993a, 1993b; McClelland & Elman, 1986; McClelland & Rumelhart, 1981; Stemmer, 1985). Crucially, in both cases interference should increase with the number of coactivated semantic neighbours (semantic neighbourhood density) and their activation levels. The activation levels of semantic neighbours depend on their semantic similarity to the target (semantic neighbourhood similarity or distance). The more semantic features neighbours share with the target and thus the more semantically similar they are, the more highly they become coactivated and the stronger they interfere with target selection at the lexical level.

One competition model that explicitly highlights the critical role of semantic neighbourhood in language production is the swinging lexical network (SLN) by Abdel Rahman and Melinger (2009). The swinging lexical network model assumes that semantic neighbours exert differential simultaneous influences at the conceptual and lexical level. Semantic activation spread between the target and its semantic neighbours at the conceptual level leads to conceptual priming (facilitation) and simultaneously to the coactivation of the target and its semantic neighbours at the lexical level, resulting

in lexical competition (interference). Naming latencies are assumed to reflect the net effects of conceptual priming and lexical competition. Interference from semantic neighbours at the lexical level should be stronger and may potentially outweigh conceptual priming when a whole cohort (a bigger number) of coactivated related items competes with the target for lexical selection. Hence, in order to predict the ease of lexical processing, one has to consider the strength and interplay of both effects: In case of target words with many compared with few semantic neighbours, lexical interference would outweigh semantic facilitation (Abdel Rahman & Melinger, 2009; Melinger & Abdel Rahman, 2013), especially when semantic neighbours are very similar (close) and therefore highly activated (e.g., Rose & Abdel Rahman, 2017).

Semantic interference with increased naming latencies for pictures named in the context of semantically related compared with unrelated representations (e.g., picture-word interference, blocked cyclic or continuous naming task, e.g., Belke, Meyer, & Damian, 2005; Damian & Als, 2005; Damian, Vigliocco, & Levelt, 2001; Glaser & Döngelhoff, 1984; Glaser & Glaser, 1989; Klein, 1964; La Heij, 1988; Schriefers, Meyer, & Levelt, 1990; Starreveld & La Heij, 1996; Vigliocco, Vinson, Damian, & Levelt, 2002)¹ were taken as evidence in favour of lexical competition models. However, recently, alternative explanations focusing on task-specific mechanisms were suggested to account for the interference effects. Specifically, in the picture-word interference task word distractors were suggested to block the articulatory output buffer, with less task-relevant unrelated words being more quickly removed than potentially response-relevant categorically related words (Mahon et al., 2007). In another non-competitive theory, a learning mechanism has been proposed to account for interference effects that were found in continuous naming and cyclic blocking tasks: here (noncompetitive) lexical selection of a target leads subsequently to a weakening of connections which link the semantic and lexical representations of competitors (Oppenheim et al., 2010).

In the present study, we chose a speeded picture-naming paradigm with manipulations of semantic neighbourhood as the key factor to reevaluate the competitive or noncompetitive nature of lexical selection. Such item-inherent variations do not require context manipulations and thus have the advantage of preventing confounding influences of additional factors associated with different context paradigms (e.g., working memory, executive control functions, response strategies). This study is the first that assessed the underlying mechanisms of lexical selection by investigating combined influences of

¹ Context paradigms are tasks in which the same target is presented in and compared across different context conditions. For example, in picture-word interference tasks, the same target picture (e.g., picture of a cat) can be paired with a semantically related distractor word (e.g., dog) or an unrelated distractor word (pear). Semantically related compared with unrelated distractor words typically lead to longer naming latencies.

semantic neighbourhood density and semantic neighbourhood similarity (distance). Different measures of semantic neighbourhood density and similarity were compared, all of which were based on shared semantic features: *Semantic neighbourhood similarity* as a measure of the mean semantic similarity between the target and all of its' semantic neighbours; *raw semantic neighbourhood density*, defined as the total number of a target word's semantic neighbours; *close semantic neighbourhood density* as a measure of semantically very similar (close) neighbours that share many semantic features with the target (e.g., similar to studies by Mirman, 2011; Mirman & Graziano, 2013); *distant semantic neighbourhood density* as a measure of semantically less similar (distant) neighbours that share only a few semantic features with the target; and *category-specific semantic neighbourhood density*, including the number of all semantic neighbours that belong to the semantic category of the target (similar to studies by Blanken, Dittmann, & Wallesch, 2002; Bormann, 2011; Bormann, Kulke, Wallesch, & Blanken, 2008).

Most of the previous studies on semantic neighbourhood effects in language production investigated only one semantic neighbourhood variable—for example, category-specific semantic neighbourhood density without controlling or taking into account semantic neighbourhood similarity. Moreover, depending on the task and tested population (language unimpaired vs. language impaired speakers), those studies revealed mixed results regarding the existence and direction of the semantic neighbourhood density effects. For example, Blanken et al. (2002), Bormann et al. (2008), and Bormann (2011) assessed how *category-specific semantic neighbourhood density* influenced picture naming in German. The density measure was obtained by asking language unimpaired participants to rate the quantity of semantically related representations that belong to the same semantic category ranging from 'many' to 'hardly any' coordinates. Blanken et al. (2002), Bormann et al. (2008) and Bormann (2011) found an effect of category-specific semantic neighbourhood density on the production of different error types in participants with aphasia and progressive anomia. Overall naming accuracy was the same for targets with many compared with few semantic neighbours; however, the former resulted in the production of more semantic errors, while the latter provoked less semantic errors but more omissions (see also Kittredge, Dell, & Schwartz, 2007a). Unlike language impaired participants, language unimpaired speakers showed no effects of category-specific neighbourhood density on naming latency and accuracy in picture naming (Bormann, 2011).

In contrast, Kittredge, Dell, and Schwartz (2007b) reported more accurate responses for words with many compared with few semantic neighbours, but no effect of error types for English speaking aphasic individuals. Unlike Blanken et al. (2002), Bormann et al. (2008), and Bormann (2011), Kittredge et al. (2007b) derived their *category-specific semantic neighbourhood density* measure from the frequency of co-

occurrence of two words in a large text corpus using the Latent Semantic Analysis database (Landauer, Foltz, & Laham, 1998). Co-occurring words were regarded as semantic neighbours if they had a semantic similarity of equal or greater than 0.4 and belonged to the same semantic category as the target word.

Similar to category-specific density, effects of *close semantic neighbourhood density* are inconsistent across studies. Mirman (2011) used the McRae, Cree, Seidenberg, and McNorgan (2005) semantic feature production norms to derive close semantic neighbourhood density scores by calculating the total number of a target's close semantic neighbours that were defined by semantic similarity values greater than 0.4, based on the number of shared semantic features between the neighbour and the target. Mirman (2011) found that naming targets with many compared with few close semantic neighbours resulted in less accurate responses and more semantic errors for aphasic and language unimpaired participants. Recently, Fieder et al. (2016) reported data from a picture-naming study with nine participants suffering from the semantic variant of primary progressive aphasia (svPPA) and a group of age-matched controls. Using the same measure for close semantic neighbourhood density as Mirman (2011), Fieder et al. (2016) found greater interference in form of less accurate naming responses and more semantic errors for words with many compared with few close semantic neighbours in both participant groups.

Rabovsky, Schad, and Abdel Rahman (2016) provided further evidence for interference by semantic neighbours when assessing effects of *intercorrelational feature density*, a different measure of semantic neighbourhood density, on picture naming in language unimpaired German speakers. Intercorrelational feature density, taken from the McRae et al. (2005) database, reflects the degree to which different feature pairs of a concept co-occur in other concepts. A greater proportion of co-occurring features (e.g., has four legs, has a tail, has fur) indicates a great semantic overlap between the target (e.g., cat) and other concepts (e.g., dog, mouse) and thus the existence of many semantic neighbours. In line with the results of Mirman (2011), Rabovsky et al. (2016) found longer naming latencies and lower accuracy for words with high intercorrelational feature density. In contrast, for semantic richness (the number of semantic features associated with a concept), facilitation with shorter naming latencies and higher accuracy was found, taken to reflect higher activation levels of target concepts and lexical entries with many compared with few semantic features.

Finally, Hameau, Biedermann, and Nickels (2018) and Hameau (2017) investigated the effects of *feature-based semantic neighbourhood density*, a combination of rated category-specific semantic neighbourhood density (see Bormann, 2011) and the number of close semantic neighbours (see Mirman, 2011) on naming in a group of aphasic and

unimpaired speakers. In line with the results of Bormann (2011), feature-based semantic neighbours did not predict naming latency and accuracy in language unimpaired speakers. However, unlike previous aphasia studies (e.g., Bormann, 2011; Mirman, 2011), a facilitative effect was found for naming accuracy: Words with many semantic neighbours were named more accurately and were less likely to result in the production of phonological errors or omissions, but not in semantic errors. Similar to Blanken et al. (2002), Bormann et al. (2008), and Bormann (2011), words with many semantic neighbours were more likely to result in the production of semantic errors than in omissions.

To summarise, only a few studies have found effects of semantic neighbourhood density that are consistent with respect to naming latency, accuracy, and/or error types and thus support lexical selection by competition (e.g., Fieder et al., 2016; Mirman, 2011; Rabovsky et al., 2016). Other studies found either no effects of semantic neighbourhood density on naming accuracy and/or latency suggesting that ease of selection is independent of neighbourhood size (e.g., Bormann, 2011), or even facilitative effects of semantic neighbourhood density, challenging the idea of competitive lexical selection (e.g., Hameau et al., 2018; Kittredge et al., 2007b).

Some of the reasons for the heterogeneous findings across semantic neighbourhood density studies may relate to the use of various different measures, each reflecting different aspects of semantic neighbourhood density, such as frequency of word co-occurrence in texts (e.g., Kittredge et al., 2007a, 2007b) and/or similarities in semantic category (e.g., Blanken et al., 2002; Bormann, 2011; Bormann et al., 2008), semantic features (e.g., Fieder et al., 2016; Mirman, 2011; Rabovsky et al., 2016), or a combination of both (e.g., Hameau et al., 2018). For example, deriving semantic neighbourhood density from the frequency of word co-occurrence in the same semantic context (Kittredge et al., 2007b) might have led to the choice of neighbours that did not only belong to the same semantic category but were additionally strong associates (e.g., cat–mouse; chair–table) while neighbours that were semantically similar but only weak associatively related (e.g., cow–horse) might have been neglected. A semantic neighbourhood density measure that is based on a combination of associative and coordinate relations could explain facilitative effects in naming (e.g., Alario, Segui, & Ferrand, 2000; La Heij, Dirks, & Kramer, 1990; but see Abdel Rahman & Melinger, 2007; Aristei, Melinger, & Abdel Rahman, 2010). In addition, methodological limitations, such as small item sets and the absence of controlling for or taking into account the full range of psycholinguistic variables (including variables such as imageability, semantic typicality, and semantic richness) could also have led to inconsistencies across studies (e.g., Alario et al., 2004; Baayen & Milin, 2010; Nickels & Howard, 1995). Moreover most of the previous studies on semantic neighbourhood effects in language production investigated only one semantic

neighbourhood variable, either category specific or close semantic neighbourhood density without controlling or taking into account others and their potential interactions (but see Hameau et al., 2018).

With regard to semantic similarity, to date there are no picture-naming studies that assessed the influence of semantic neighbourhood similarity on naming in the form of a target item-inherent variation and thus without context manipulations. So far, the influence of semantic neighbourhood similarity has only been investigated in the context of semantically more compared with semantically less similar representations (Aristei et al., 2010; Lee & de Zubicaray, 2010; Mahon et al., 2007; Vigliocco, Vinson, Lewis, & Garrett, 2004). For example, graded effects of semantic similarity (distance) were found in picture-word interference tasks with greater interference when naming target pictures that were presented with semantically very similar distractor words compared with semantically less similar distractor words (e.g., Vigliocco et al., 2004; but see Hutson & Damian, 2014; Mahon et al., 2007).

The present study aimed to investigate the influence of semantic neighbourhood density and semantic neighbourhood similarity on naming performance, with a focus on the question of how semantic neighbourhood similarity may influence effects of semantic neighbourhood density while taking into account influences of other lexically and semantically relevant variables. A large set of 180 items was tested, and all variables including semantic neighbourhood were analysed as continuously varying in order to prevent artefacts due to small and unusual item sets that can result from extensive matching (e.g., see Hauk, Davis, Ford, Pulvermüller, & Marslen-Wilson, 2006; Rabovsky et al., 2016). A speeded picture-naming task was used as it was found to be suitable to assess errors in language production that are similar to the errors of language impaired speakers (e.g., Hodgson & Lambon Ralph, 2008; Kello, 2004; Kello & Plaut, 2010; Mirman, 2011), and thus to find further converging evidence for semantic neighbourhood effects not only on naming latencies and accuracy but also on semantic errors and omissions.

If lexical selection is competitive,² we predict to find interference due to an increase in lexical competition with an increasing number of a target's semantic neighbours. Specifically, we hypothesize that words with more semantic neighbours are produced slower, less accurately, and are associated with an increase of naming errors that have their origin at the semantic and/or lexical level including semantic errors and/or omissions compared with words with fewer semantic neighbours. With regard to lexical-semantic errors, we might predict to find a similar number of semantic errors and

² Please note that the predictions for lexical competition in the speeded picture-naming task, a task that does not involve semantic context manipulations, are similar for different language production theories (e.g., Abdel Rahman & Melinger, 2009; Levelt et al., 1999; Roelofs, 2018; Wheeldon & Monsell, 1994).

omission errors. Alternatively, a steeper increase of semantic errors compared with omissions could also be predicted since an increasing number of semantic neighbours not only enhances lexical competition but might also raise the probability of selecting erroneously a semantic neighbour rather than resulting in a selection failure and thus an omission error at the lexical level. We do not expect to find effects of semantic neighbourhood density for the production of other error types, that are not the direct result of processing at the semantic or lexical (lexical-syntactic, lemma) level, including phonological errors and semantically and phonologically unrelated errors. Concerning semantic neighbourhood similarity, an increasing semantic overlap (similarity) between the target and its semantic neighbours should result in a stronger coactivation of competitors at the lexical level. Therefore, the network should be most highly active—and competition should be strongest—when a big cohort of closely related (and thus, strongly coactivated) competitors is active (Abdel Rahman & Melinger, 2009), resulting in enhanced semantic neighbourhood effects (effects of semantic neighbourhood similarity) with increasing semantic overlap. Hence, we expect that the likelihood of producing semantic errors and/or omissions increases for words with semantically more similar neighbours compared with words with semantically less similar neighbours.

In contrast, if lexical selection is noncompetitive, no effects of semantic neighbourhood density or semantic neighbourhood similarity on naming should be found since semantic neighbours do not compete with the target for selection. If anything, facilitation due to conceptual priming of the target by its semantic neighbours might occur.

Method

Participants

Thirty participants (24 females) with a mean age of 25 years (ranging from 19 to 34 years) gave informed consent to take part in this study in exchange for course credits or 7€/hour. The number of participants was based on a previous study of semantic neighbourhood density in language production (e.g., Mirman, 2011) in which the same speeded picture-naming paradigm was used. The study was approved by the local ethics committee of the Humboldt-Universität zu Berlin. All participants were native speakers of German with normal or corrected-to-normal vision and no history of language impairment.

Materials

Stimuli consisted of 180 coloured photographs of objects. All stimuli were chosen from the British database for concept

property norms by Devereux, Tyler, Geertzen, and Randall (2014). Stimuli in the database were excluded, if they were abstract/low imageable and therefore hard to depict (e.g., codeine, penicillin) or not very well known in the German culture (e.g., satsuma). Stimuli were further excluded if their German translation resulted in a morphologically complex word (e.g., compounds), a homophone (e.g., English: ‘castle’; German: ‘Schloss’ with the word meaning ‘castle’ or ‘lock’), a synonym (e.g., English: ‘orange’; German: ‘Apfelsine’ or ‘Orange’), or in the same word twice (e.g., while English has two words for ‘pigeon’ and ‘dove’, German has only one word, ‘Taube’).

Information on semantic neighbourhood variables for each stimulus was obtained from the database for concept property norms by Devereux et al. (2014). Data for the concept property norms were collected by asking participants to generate semantic features for given words (concepts). Semantic features were analysed, and a feature vector was calculated for each word which was weighted for the features’ production frequencies—the number of participants that generated a certain feature for a concept. Devereux et al. (2014) created a word–feature matrix by combining all of the semantic features across words/concepts. Features which were generated fewer than five times for a given concept in the matrix were excluded. Semantic similarity between two concepts was calculated as the cosine between their two production frequency vectors, which varied from zero (for no shared semantic features) to one (for identical semantic feature vectors). Information on semantic similarity was used to identify the number of semantic neighbours (semantic neighbourhood density) and the similarity of semantic neighbours to their target (semantic neighbourhood similarity; for a similar procedure, see McRae et al., 2005).

Raw semantic neighbourhood density was measured by the number of concepts that have a similarity to the target of greater than zero. For example, the target ‘Pfirsich’ (peach) has semantic neighbours, such as nectarine, plum, melon, apple, carrot, potato, jam, and ball. *Semantic neighbourhood similarity (distance)* was defined as the mean cosine between the target’s feature vector and the different feature vectors of all of the target’s semantic neighbours, similar to the definition by Mirman and Magnuson (2008). For example, the target ‘Pfirsich’ (peach) has a relatively high semantic neighbourhood similarity of 0.130 and thus semantically very similar neighbours, while the target ‘Gürtel’ (belt) has a relatively low semantic neighbourhood similarity of 0.064 and thus semantically less similar neighbours (see Appendix Table 6 for the full list of target stimuli and their semantic neighbourhood values).

Beside raw semantic neighbourhood density, additional, more in-depth analyses were run with three more specific semantic neighbourhood density measures in order to assess whether semantic neighbourhood density affects naming

performance if semantic neighbours exceed a certain degree of semantic similarity. As mentioned earlier, semantic similarity between two concepts can vary between zero (for no shared semantic features) and one (for identical semantic feature vectors). Semantic neighbourhood similarity between the target and each neighbour was used to categorise semantic neighbours as either semantically close or distant to a target by converting the continuous variable of semantic similarity into a categorical variable with two equally spaced intervals: 0–0.5, 0.5–1.0. Subsequently the sum of the total number of neighbours within each category was calculated to create the two different density variables: The number of semantically close neighbours (*close semantic neighbourhood density*) including neighbours with a similarity between 0.5 and 1.0 (for a similar measure, see Mirman & Magnuson, 2008) and the number of semantically distant neighbours (*distant semantic neighbourhood density*) including neighbours with a similarity between zero and 0.5.

In addition to close and distant semantic neighbourhood density, we included a *category-specific semantic neighbourhood density* measure that comprised the number of all semantic neighbours that belong to the same semantic category as the target (similar to studies by Blanken et al., 2002; Bormann, 2011; Bormann et al., 2008). For example, the target ‘Pfirsich’ (peach) has 16 category-specific semantic neighbours, such as nectarine, plum, melon, apple, lemon, and strawberry. The majority (85%) of close semantic neighbours were from the same semantic category and were thus coordinates of the targets, while most of the category-specific neighbours (90.68%) from the category-specific semantic neighbourhood density measure were not semantically close (similarity of less than 0.5) to the target and thus were not included in the close semantic neighbourhood density measure. The category-specific semantic neighbourhood density variable was used to disentangle whether an influence of close semantic neighbourhood density can be ascribed to the number of semantically similar neighbours or alternatively to the neighbours’ taxonomical relatedness to the target. In case of the latter, we would expect to find interfering effects on naming performance from close and/or category-specific semantic neighbourhood density.

The concept property norms by Devereux et al. (2014) were further used to derive information about the semantic richness of each target word which was defined as the number of a target’s semantic features. Information about other psycholinguistic variables was taken from the following databases: spoken lemma frequency and word length in form of the number of phonemes from the German dlexDB database (Heister et al., 2011). Data for imageability, semantic typicality, familiarity, age of acquisition, and visual complexity were obtained through ratings by the authors. For concept familiarity and visual complexity, 17 participants were asked to rate the

depicted objects using the instructions from Gilhooly and Hay (1977). For age of acquisition, semantic typicality, and imageability, 10 participants were asked to rate the stimuli names using instructions by Schröder, Gemballa, Ruppin, and Wartenburger (2012) and Alario and Ferrand (1999).³ All of the experimental stimuli were further controlled for name agreement in order to prevent naming difficulties from arising through uncertainty in identifying the depicted objects (e.g., Cheng, Schafer, & Akyurek, 2010). Seventeen participants provided measures of naming accuracy in a picture-naming experiment in which they were instructed to name the pictures as accurately as possible. Only pictures which were named with above 80% name agreement (Mean = 97.09; *SD* = 4.59) were included in this study (see Appendix Table 7).

Design and procedure

Participants were tested individually in a quiet room. Pictures were displayed on a white background in the centre of a computer screen. At the beginning of the experiment, participants were instructed that prior to the presentation of the picture they would hear a series of three beeps in combination with numbers which count down from 3, 2, 1. On the fourth beep they saw the picture and were asked to name it as quickly as possible before the fifth beep and the number zero appeared. Each of these time windows were 500-ms long. After the presentation of the number zero, a blank screen appeared for 1,000 ms. For a visual presentation of the different time windows within a trial, see Fig. 1.

Naming latencies were measured by means of a voice key, which was activated at the onset of the target presentation. Vocal responses were recorded until the timeout of 2,000 ms. All of the audio-recorded response trials were transcribed and checked for accuracy and timing using CheckVocal⁴ (Protopapas, 2007) to ensure that the voice-trigger mechanism had correctly registered the beginning of the response. Trials which were mistriggered (e.g., through lip smacking, heavy breathing, movements

³ Because of their lengths, the ratings for the different variables were conducted in two different testing sessions with the same participants—one session to rate concept familiarity and visual complexity and one session to rate age of acquisition, semantic typicality, and imageability. Some of the participants who participated in the first session could not attend the second testing session resulting in different participant numbers for the ratings.

⁴ CheckVocal is a program which aims to facilitate the manual processing of spoken responses. It determines response accuracy, and it also ensures that the voice-trigger mechanism has correctly registered the participant’s naming response, because it is very likely that voice keys are triggered by nonspeech sounds made by the participant prior to the response (e.g., lip smacking, coughing, hesitation fillers), or late responses to the preceding items. Although it is possible to exclude some sources of timing errors by setting absolute thresholds (e.g., discarding response times below 100 ms or above a certain delay), it is not possible to ensure reliable response times entirely automatically (Protopapas, 2007).

Fig. 1 Diagram of the course of events for a single trial in the speeded picture-naming task.

or sound volume) were adjusted. Trial sequences during the experiment were controlled by DMDX (Forster & Forster, 2003).

The experiment began with 20 practice trials in which participants named pictures that were not part of the 180 critical stimuli. After each practice trial, participants could take a break to ask questions or receive feedback if necessary. All of the 180 pictures were distributed evenly across two blocks. The order of the blocks was counterbalanced across participants. The order of stimuli within each block was randomised. Participants received the two blocks with a short break between blocks. The entire experiment lasted approximately 20 minutes.

Response coding

The first full response was coded. A full naming response was defined as consisting of at least one possible German syllable. A response was coded as correct if it consisted of the correctly pronounced target word or of a word that is an acceptable alternative response for the target (e.g., response: ‘Henne’ [hen] for target: ‘Huhn’ [chicken]).

Incorrect responses were coded as semantic errors if they consisted of a word that is semantically related to the target by belonging to the same semantic category, such as superordinates (e.g., ‘Blume’ [flower] for ‘Tulpe’ [tulip] and coordinates (e.g., ‘Strauß’ [ostrich] for ‘Pfau’ [peacock]), or by belonging to a different semantic category, such as associates (e.g., ‘Wüste’ [desert] for ‘Pyramide’ [pyramid]), concepts that stand in a part-whole relationship to the target (e.g., ‘Nadel’ [needle] for ‘Spritze’ [veil]) and semantic other for semantically related responses that could not be easily categorised (e.g., ‘Gemüse’ [vegetable] for ‘Petersilie’ [parsley]). False starts that shared 50% or more of their phonemes with a semantically related representation were also coded as

semantic errors (e.g., ‘Lö [Löwe]’ [lion] for the target ‘Tiger’ [tiger]). However, we are aware that some response types cannot be unambiguously classified as (semantic) errors that resulted from faulty processing at the lexical and/or semantic level. For example, since participants were not familiarised with the stimuli’s names prior to testing, superordinate errors and errors in a part-whole relationship to the target could have resulted from a misunderstanding of the level of the desired response. One response type that can be clearly classified as semantic error are coordinates of the target. Therefore, in addition to a general semantic error analysis, we ran a separate analysis with coordinate errors only.

Omissions were instances where the participants failed to respond or made a comment that expressed a failure to respond (e.g., ‘I don’t know’). Other error types were responses (words and nonwords) that had no semantic relationship to the target including unrelated errors and false starts (e.g., ‘Shop’ [shop] for ‘Kutsche’ [carriage]; nonword ‘/ro:/’ for ‘Sarg’ [coffin]), phonological errors and false starts that shared a minimum of 50% of their phonemes with the target (e.g., nonword ‘/kank/’ for ‘Anker’ [anchor]; nonword ‘/pa:/’ for ‘Spargel’ [asparagus]; see Appendix Table 8 for a complete list of participants’ error responses).

Analysis

The analysis of the picture-naming latency data (RT) was performed using linear mixed-effects modelling as implemented in the lme4 package (Bates, Maechler, Bolker, & Walker, 2014) in the statistical software R (Version 3.2.1; R Core Team, 2014). We started with a full model including 11 fixed factors: semantic neighbourhood similarity, raw semantic neighbourhood density, semantic richness, semantic typicality, imageability, familiarity, age of acquisition, lemma frequency, visual complexity, length (number of phonemes), and presentation order. All variables were centered and scaled. Random variation by specific items and participants was accounted for by entering items and participants with random intercepts. In a first step, a stepwise backward elimination procedure was used to remove all variables, except for the semantic neighbourhood variables, that did not improve the model’s fit significantly in order to assess and consider the influence of language relevant psycholinguistic variables. In a second step, individual effects of each semantic neighbourhood variable in the presence of the other semantic neighbourhood variable and the remaining psycholinguistic variables was analysed by excluding only one of the two semantic neighbourhood variables at the time. Log-likelihood ratio tests were used to compare the models’ fit throughout Steps 1 and 2. The summary of the final model which includes only the significant

psycholinguistic and semantic neighbourhood variables is reported, and p values were determined using the package lmerTest (Kuznetsova, Brockhoff, & Christensen, 2014).

For the additional, more specific semantic neighbourhood density analyses, the three semantic neighbourhood density variables (close semantic neighbourhood density, distant semantic neighbourhood density, and category-specific semantic neighbourhood density) were inserted into the original reduced base model which included only the psycholinguistic control variables that proved to be significant (but excluded the previous semantic neighbourhood variables: raw semantic neighbourhood density and semantic neighbourhood similarity). A backward elimination procedure was used where only one of the three semantic neighbourhood variables were excluded at the time. The fit between the reduced and the more complex model was compared using log likelihood ratio tests.

The error analyses were performed using the same principles as the naming latency analyses. We used generalised linear mixed-effects models for binomial outcomes to analyse the influence of psycholinguistic variables on naming accuracy and the production of different error types in the base model, and the influence of variables of semantic neighbourhood in the advanced model using the function glmer as part of the R package lme4 (Bates et al., 2014). Separate models were fitted with different dependent variables including accuracy (correct vs. incorrect responses), number of semantic errors versus correct responses, number of coordinate errors versus correct responses and number of omissions versus correct responses. Due to the small number of phonological and unrelated errors an analysis including other error types versus correct responses could not be performed. For the analyses of the different error types, separate binomial analyses were conducted as no standard exists yet for mixed multinomial analyses (for similar analyses, see also Hameau, 2017; Hameau et al., 2018; Jaeger, Furth, & Hilliard, 2012). For each separate binomial analysis, the errors of interest (e.g., semantic errors) were coded as zero and compared with correct responses coded as one. Responses/errors that were not part of the specific analyses were excluded by leaving their coding blank. We further assessed whether the different semantic neighbourhood variables predicted the probability of producing a semantic error (coded as 1) over an omission (coded as 0; see Bormann, 2011; Hameau et al., 2018).

Results

Descriptive analyses

Trials in which participants produced naming errors including omissions (985 data points, 18.24%) were

Table 1 Overall rate of correct responses and different error types

Response type	Overall error rate (%)
Correct responses	81.76
Semantic errors (coordinate errors)	11.80 (9.44)
Omissions	5.26
Other errors (including phonological errors and unrelated errors)	1.19

excluded for the naming latency analysis. Trials where naming latencies were faster than 300 ms, and those which were more than three standard deviations above or below the mean of the participant (76 data points, 1.72%) were removed. Table 1 gives an overview of the different response/error types (correct responses, semantic errors, coordinate errors, omissions, and other error types). There was no correlation between raw semantic neighbourhood density and semantic neighbourhood similarity, nor between close semantic neighbourhood density, distant semantic neighbourhood density and category-specific semantic neighbourhood density (see Appendix Table 9).

Latency analyses

RTs were transformed to approximate normal distribution using a reciprocal transformation (power -0.735) as indicated by the Box-Cox test. The reduced model included familiarity, age of acquisition, lemma frequency, and presentation order as significant predictors of naming latencies. Naming slowed down for words that were less familiar, less frequent, and acquired later in life. Naming latencies increased further with the progression of the experiment. The exclusion of the remaining, nonsignificant psycholinguistic variables (semantic richness, semantic typicality, imageability, length, and visual complexity) did not reduce the goodness of fit, $\chi^2(5) = 2.229$, $p = .817$, but instead increased the fit of the model as indicated by the lower AIC and BIC values (AIC: full model: -59227 vs. reduced model: -59235 ; BIC: full model: -59132 vs. reduced model: -59171). Neither semantic neighbourhood similarity, $\chi^2(1) = 0.791$, $p = .374$, nor raw semantic neighbourhood density, $\chi^2(1) = 0.106$, $p = .745$, were significant predictors of naming latency. There was no significant interaction between raw semantic neighbourhood density and semantic neighbourhood similarity, $\chi^2(1) = 1.027$, $p = .311$. For details of the final model, see Table 2.

The more detailed analysis of semantic neighbourhood density revealed a significant effect of close semantic neighbourhood density, $\chi^2(1) = 5.216$, $p = .022$, while

Table 2 LMM statistics with the final model including only significant variables for naming latency (reciprocal transformed)

Model including originally raw semantic neighbourhood density and semantic neighbourhood similarity					
<i>Random effects:</i>					
Subject	(Intercept)	1.66E-08	0.0001		
Items	(Intercept)	2.13E-08	0.0001		
Residual		6.12E-08	0.0002		
<i>Fixed effects:</i>					
(Intercept)	Estimate	SE	df	t value	p value
	1.40E-03	2.72E-05	48	51.453	<.001
Familiarity	1.77E-04	4.16E-05	174	4.258	<.001
AoA	−1.94E-04	3.67E-05	170	−5.300	<.001
Lemma frequency	4.18E-05	1.35E-05	170	3.096	.002
Presentation order	−1.43E-05	3.79E-06	4147	−3.773	<.001
More specific model of semantic neighbourhood density including originally close, distant, and category-specific semantic neighbourhood density					
<i>Random effects:</i>					
Subject	(Intercept)	1.66E-08	0.0001		
Items	(Intercept)	2.08E-08	0.0001		
Residual		6.12E-08	0.0002		
<i>Fixed effects:</i>					
(Intercept)	Estimate	SE	df	t value	p value
	1.40E-03	2.71E-05	48	51.599	<.001
Close SN-Density	−2.43E-05	1.17E-05	175	−2.075	.039
Familiarity	1.86E-04	4.15E-05	173	4.497	<.001
AoA	−1.94E-04	3.63E-05	169	−5.345	<.001
Lemma frequency	3.82E-05	1.35E-05	169	2.838	.005
Presentation order	−1.43E-05	3.79E-06	4148	−3.765	<.001

neither distant semantic neighbourhood density,⁵ $\chi^2(1) = 0.283$, $p = .595$, nor category-specific semantic neighbourhood density, $\chi^2(1) = 1.654$, $p = .198$, were significant predictors of naming speed. Naming slowed down for words with many close semantic neighbours (see Table 2).

⁵ Since target words comprised a much larger range of distant semantic neighbourhood density (ranging from 28 to 445 distant semantic neighbours) compared with close semantic neighbourhood density (ranging from zero to 25 close semantic neighbours) and category-specific semantic neighbourhood density (ranging from zero to 102 category-specific semantic neighbours), an additional analysis was run to test for a potential nonlinear effect of distant semantic neighbourhood density. In this analysis we compared the original reduced linear base model which included the three semantic neighbourhood density variables (close semantic neighbourhood density, distant semantic neighbourhood density, and category-specific semantic neighbourhood density) with a similar, but more complex, nonlinear (quadratic) model using the poly() function for distant semantic neighbourhood density (poly(distant semantic neighbourhood density, degree = 2)). The log-likelihood ratio test was used to compare the two models. None of the comparisons reached significance, confirming an absence of a nonlinear effect of distant semantic neighbourhood density on naming latency, $\chi^2(1) = 2.814$, $p = .093$, naming accuracy, $\chi^2(1) = 2.184$, $p = .139$, correct responses compared to semantic errors, $\chi^2(1) = 1.849$, $p = .174$, correct responses compared with coordinate errors, $\chi^2(1) = 0.249$, $p = .618$, correct responses compared with omissions, $\chi^2(1) = 2.456$, $p = .117$, and omissions compared with semantic errors, $\chi^2(1) = 0.315$, $p = .575$.

Error analyses

Correct responses versus incorrect responses The reduced model included familiarity, age of acquisition and semantic typicality as significant predictors of naming accuracy. Words that were more typical exemplars of a semantic category, very familiar, and acquired early in life resulted in more accurate naming responses. The exclusion of the remaining variables did not result in a significant reduction of the goodness of fit, $\chi^2(6) = 4.885$, $p = .559$, but instead in a slightly better fit (AIC: full model: 4063 vs. reduced model: 4056; BIC: full model: 4155 vs. reduced model: 4109). Semantic neighbourhood similarity, $\chi^2(1) = 6.445$, $p = .011$, but not raw semantic neighbourhood density, $\chi^2(1) = 0.289$, $p = .591$, improved the model's fit significantly. Words with semantically more similar neighbours led to a decrease of naming accuracy compared with words with semantically less similar neighbours (see Fig. 2 and Table 3). There was no significant interaction between raw semantic neighbourhood density and semantic neighbourhood similarity, $\chi^2(1) = 0.517$, $p = .472$.

The more detailed analysis of semantic neighbourhood density revealed a significant effect of close semantic neighbourhood density, $\chi^2(1) = 9.993$, $p = .002$, while neither distant semantic neighbourhood density, $\chi^2(1) = 0.143$, $p = .706$, nor category-specific semantic neighbourhood density, $\chi^2(1) = 0.848$, $p = .357$, were significant predictors of naming accuracy. Naming accuracy decreased for words with many close semantic neighbours. Details of the final model can be found in Table 3.

Correct responses versus semantic errors The reduced model included familiarity and age of acquisition. The likelihood of producing semantic errors compared with accurate responses increased for words that were less familiar and acquired later in life. Reducing the model by excluding the remaining variables did not result in a significant drop in goodness of fit, $\chi^2(7) = 10.408$, $p = .167$, but rather in an improvement (AIC: full model: 2939 vs. reduced model: 2935; BIC: full model: 3030 vs. reduced model: 2981). Similar to accuracy, the model's fit was significantly improved by semantic neighbourhood similarity, $\chi^2(1) = 4.325$, $p = .038$, but not by raw semantic neighbourhood density, $\chi^2(1) = 0.151$, $p = .697$ (see Fig. 2 and Table 4). The likelihood of producing a semantic error over a correct response increased for words with semantically more similar neighbours. There was no significant interaction between raw semantic neighbourhood density and semantic neighbourhood similarity, $\chi^2(1) = 0.152$, $p = .697$.

The results of the more detailed analysis of semantic neighbourhood density showed a significant effect of close semantic neighbourhood density, $\chi^2(1) = 6.577$, $p = .010$, but neither of distant semantic neighbourhood

Fig. 2 Effect of semantic neighbourhood similarity on naming accuracy (accurate vs. inaccurate responses); semantic errors (coded as 1) versus accurate responses (coded as 0); coordinate errors (coded as 1) versus accurate responses (coded as 0); and omissions (coded as 1) versus accurate responses (coded as 0) depicted as logistic regression lines

with 95% confidence intervals. Points indicate average number of accurate responses; semantic errors; coordinate errors; or omissions for each subject for three equal-sized bins of semantic neighbourhood similarity

density, $\chi^2(1) = 0.088$, $p = .767$, nor category-specific semantic neighbourhood density, $\chi^2(1) = 0.057$, $p =$

Table 3 LMM statistics with the final model including only significant variables for naming accuracy (accurate (1) – inaccurate responses (0))

Model including originally raw semantic neighbourhood density and semantic similarity				
<i>Random effects:</i>	Name	Variance	SD	
Subjects	(Intercept)	0.4216	0.6493	
Items	(Intercept)	1.6424	1.2816	
<i>Fixed effects:</i>	Estimate	SE	z value	p value
(Intercept)	2.0736	0.1775	11.684	<.001
SN-Similarity	−0.2797	0.1106	−2.528	.011
Typicality	−0.5707	0.2850	−2.003	.045
Familiarity	1.1449	0.3857	2.969	.003
AoA	−1.2235	0.4518	−2.708	.007
More specific model of semantic neighbourhood density including originally close, distant, and category-specific semantic neighbourhood density				
<i>Random effects:</i>	Name	Variance	SD	
Subjects	(Intercept)	0.4213	0.6491	
Items	(Intercept)	1.5855	1.2591	
<i>Fixed effects:</i>	Estimate	SE	z value	p value
(Intercept)	2.0782	0.1762	11.797	<.001
Close SN-Density	−0.3576	0.1096	−3.262	.001
Typicality	−0.6984	0.2851	−2.449	.014
Familiarity	1.3224	0.3847	3.437	<.001
AoA	−1.0679	0.4495	−2.376	.018

.811. The likelihood of producing a semantic error over an accurate response increased for words with many close semantic neighbours (see Table 4 for the final model).

Correct responses versus coordinate errors The reduced base model included familiarity as a significant predictor and age of acquisition as marginally significant predictor for the production of coordinate errors in the reduced model. The likelihood of producing a coordinate error over an accurate response increased for words that were less familiar and acquired later in life. Exclusion of the nonsignificant variables did not result in a significant reduction in goodness of fit, $\chi^2(7) = 7.370$, $p = .391$, but rather in an improvement (AIC: full model: 2483 vs. reduced model: 2477; BIC: full model: 2575 vs. reduced model: 2522). Semantic neighbourhood similarity, $\chi^2(1) = 4.950$, $p = .026$, but not raw semantic neighbourhood density, $\chi^2(1) = 1.627$, $p = .202$, was once again the only significant semantic neighbourhood predictor of coordinate errors leading to a higher likelihood of producing a coordinate error instead of a correct response for words with semantically more similar neighbours (see Fig. 2 and Table 4). There was no significant interaction between the two semantic neighbourhood variables, $\chi^2(1) = 0.270$, $p = .604$.

Table 4 LMM statistics with the final model including only significant variables for semantic errors and coordinate errors compared with accurate responses (accurate responses (1) – semantic/coordinate errors (0))

Semantic errors—model including originally raw semantic neighbourhood density and semantic similarity				
<i>Random effects:</i>	Name	Variance	SD	
Subjects	(Intercept)	0.3707	0.6088	
Items	(Intercept)	2.9123	1.7065	
<i>Fixed effects:</i>	Estimate	SE	z value	p value
(Intercept)	2.918	0.2172	13.437	<.001
SN-Similarity	−0.3081	0.1498	−2.056	.040
Familiarity	1.1221	0.5204	2.156	.031
AoA	−2.2167	0.4846	−4.574	<.001
Semantic errors—more specific model of semantic neighbourhood density including originally close, distant, and category-specific semantic neighbourhood density				
<i>Random effects:</i>	Name	Variance	SD	
Subjects	(Intercept)	0.3698	0.6081	
Items	(Intercept)	2.8535	1.6892	
<i>Fixed effects:</i>	Estimate	SE	z value	p value
(Intercept)	2.9305	0.2162	13.551	<.001
Close SN-Density	−0.3813	0.1465	−2.603	.009
Familiarity	1.2881	0.5214	2.471	.013
AoA	−2.2083	0.4785	−4.615	<.001
Coordinate errors—model including originally raw semantic neighbourhood density and semantic similarity				
<i>Random effects:</i>	Name	Variance	SD	
Subjects	(Intercept)	0.4094	0.6398	
Items	(Intercept)	3.3371	1.8268	
<i>Fixed effects:</i>	Estimate	SE	z value	p value
(Intercept)	3.3867	0.2429	13.94	<.001
SN-Similarity	−0.3521	0.1652	−2.131	.033
Familiarity	1.335	0.5774	2.312	.021
AoA	−1.7408	0.5195	−3.351	<.001
Coordinate errors—more specific model of semantic neighbourhood density including originally close, distant, and category-specific semantic neighbourhood density				
<i>Random effects:</i>	Name	Variance	SD	
Subjects	(Intercept)	0.4087	0.6393	
Items	(Intercept)	3.3228	1.8229	
<i>Fixed effects:</i>	Estimate	SE	z value	p value
(Intercept)	3.3925	0.2425	13.987	<.001
Close SN-Density	−0.3543	0.1612	−2.198	.030
Familiarity	1.482	0.5812	2.550	.011
AoA	−1.771	0.5161	−3.431	<.001

In the more specific analysis of semantic neighbourhood density a significant effect of close semantic neighbourhood density, $\chi^2(1) = 5.253$, $p = .022$, but not of distant semantic neighbourhood density, $\chi^2(1) = 1.404$, $p = .236$, or category-specific semantic neighbourhood density, $\chi^2(1) = 0.001$, $p = .976$, was found. The probability of naming a target picture

with a coordinate error instead of a correct response increased for words with many close semantic neighbours (see Table 4 for the final model).

Correct responses versus omissions The reduced model included semantic typicality and familiarity as significant predictors and age of acquisition as a marginally significant predictor of omissions. Items that were less typical, less familiar, and acquired later in life were more likely to result in an omission than in an accurate response. None of the other linguistic variables improved the model's fit significantly, $\chi^2(6) = 3.724$, $p = .714$. The exclusion of the nonsignificant variables resulted in a better fit (AIC: full model: 1668 vs. reduced model: 1660; BIC: full model: 1758 vs. reduced model: 1711). Similar to semantic and coordinate errors, only semantic neighbourhood similarity, $\chi^2(1) = 7.935$, $p = .005$, but not raw semantic neighbourhood density, $\chi^2(1) = 0.289$, $p = .591$, was a significant predictor of omissions. Words with semantically more similar neighbours were more likely to result in an omission error than to be named correctly (see Fig. 2 and Table 5). No significant interaction was found between the two semantic neighbourhood variables, $\chi^2(1) = 2.594$, $p = .107$.

Table 5 LMM statistics with the final model including only significant variables for omissions compared with accurate responses (accurate responses (1) – omissions (0)) and for semantic errors compared with omissions (semantic errors (1) – omissions (0))

Omissions—model including originally raw semantic neighbourhood density and semantic similarity				
<i>Random effects:</i>	Name	Variance	SD	
Subjects	(Intercept)	1.368	1.169	
Items	(Intercept)	1.403	1.185	
<i>Fixed effects:</i>	Estimate	SE	z value	p value
(Intercept)	3.8649	0.2819	13.712	<.001
SN-Similarity	−0.3482	0.1235	−2.819	.005
Typicality	−0.8101	0.3321	−2.439	.015
Familiarity	1.2520	0.4334	2.889	.004
AoA	−0.9136	0.5179	−1.764	.078
Omissions—more specific model of semantic neighbourhood density including originally close, distant, and category-specific semantic neighbourhood density				
<i>Random effects:</i>	Name	Variance	SD	
Subjects	(Intercept)	1.368	1.170	
Items	(Intercept)	1.395	1.181	
<i>Fixed effects:</i>	Estimate	SE	z value	p value
(Intercept)	3.8626	0.2817	13.713	<.001
Close SN-Density	−0.3348	0.1256	−2.666	.008
Typicality	−0.9408	0.3396	−2.770	.006
Familiarity	1.4367	0.4411	3.257	.001
AoA	−0.7785	0.5250	−1.483	.138
Semantic errors versus omissions—same final model for both analyses				
<i>Random effects:</i>	Name	Variance	SD	
Subjects	(Intercept)	1.581	1.257	
Items	(Intercept)	1.808	1.345	
<i>Fixed effects:</i>	Estimate	SE	z value	p value
(Intercept)	1.3541	0.2896	4.676	<.001
Lemma frequency	0.4421	0.178	2.484	.013

In the more detailed analysis of semantic neighbourhood density, only close semantic neighbourhood density, $\chi^2(1) = 6.461$, $p = .011$, but neither distant semantic neighbourhood density, $\chi^2(1) = 0.139$, $p = .710$, nor category-specific semantic neighbourhood density, $\chi^2(1) = 0.781$, $p = .377$, reached significance. Naming of words with many close semantic neighbours was more likely to result in an omission error than in an accurate response compared with words with few close semantic neighbours (see Table 5 for the final model).

Semantic errors versus omissions Lemma frequency was a significant predictor for the production of semantic errors over omissions: Participants were more likely to produce semantic errors than omissions for words of higher frequency. The exclusion of the remaining psycholinguistic variables did not change the model's goodness of fit, $\chi^2(8) = 6.032$, $p = .644$, but resulted in a slightly better fit (AIC: full model: 936 vs. reduced model: 926; BIC: full model: 1004 vs. reduced model: 955). Neither raw semantic neighbourhood density, $\chi^2(1) = 0.026$, $p = .872$, nor semantic neighbourhood similarity, $\chi^2(1) = 0$, $p = 1.00$, and their interaction, $\chi^2(1) = 0.522$, $p = .470$, were significant (see Table 5).

In the more specific analysis of semantic neighbourhood density, none of the semantic neighbourhood density variables were significant predictors for the production of semantic errors over omissions, close semantic neighbourhood density: $\chi^2(1) = 1.972$, $p = .160$; distant semantic neighbourhood density: $\chi^2(1) = 0.0003$, $p = .987$; category-specific semantic neighbourhood density: $\chi^2(1) = 0$, $p = .996$.

General discussion

In this study we investigated the combined influences of semantic neighbourhood density and semantic neighbourhood similarity (distance). Influences of other important lexical and semantic variables were considered. We found consistent evidence for an influence of semantic neighbourhood similarity (distance) on naming accuracy and also on the production of different lexical-semantic error types. Words with semantically more similar neighbours increased picture-naming errors and resulted therefore in significantly less accurate naming responses and a higher likelihood of producing semantic errors and omissions over accurate responses. However, no significant influence of semantic neighbourhood similarity on naming latency was found—a result that could be explained by the speeded picture naming paradigm and thus the pressure to name pictures with high speed in terms of a ceiling effect. Similar to our study, Mirman (2011) conducted a speeded picture-naming task and found only a significant semantic neighbourhood effect for the accuracy of naming responses but not their speed. One explanation for the sole effect of

semantic neighbourhood similarity on naming accuracy is the threshold account by Mirman (2011), according to which participants lower the lexical threshold of words during the speeded picture-naming task in order to generate responses more quickly, leading to partly incomplete and thus more error prone lexical processing.

The lexical and/or semantic origin of semantic errors and omissions in our task was confirmed by the influence of other lexical-semantic variables including familiarity, age of acquisition, and semantic typicality on the production of those errors. In line with previous studies, we found that the probability of producing semantic errors compared with accurate responses increased for words that are less familiar and/or acquired later in life (e.g., Cuetos, Aguado, Izura, & Ellis, 2002; Nickels & Howard, 1995). Similarly, the likelihood of producing omissions over accurate responses increased for words that are less familiar, acquired later in life, and/or less typical exemplars of a semantic category. This confirmed that effects of semantic neighbourhood similarity (distance) unfold at earlier stages of processing including the conceptual (semantic) and lexical level.

In line with our first prediction for lexical-semantic errors, none of the semantic neighbourhood variables determined the production of semantic errors over omissions. Instead, lemma frequency was the only variable that determined whether erroneous naming resulted in a semantic rather than an omission error with high frequency words being more likely to be named with a semantic error than an omission error. In addition to the other (Fig. 3) results for correct responses versus semantic errors and correct responses versus omissions, this can be taken as evidence for both error types (i.e., semantic errors, omissions) being similarly affected by semantic neighbourhood similarity (distance).

Unlike for semantic neighbourhood similarity (distance), we did not find an effect of raw semantic neighbourhood density. That is, picture-naming performance did not change with the total number of semantic neighbours. Furthermore, no interaction was found between raw semantic neighbourhood density and semantic neighbourhood similarity (distance) which indicates that semantic neighbourhood similarity does not modulate the influence of our specific (raw) semantic neighbourhood density measure on naming performance. In other words, we cannot conclude that interference by raw semantic neighbourhood density grows stronger with an increasing similarity of those neighbours. However, possible reasons for the absence of a raw semantic neighbourhood density effect and the missing interaction between raw semantic neighbourhood density and semantic neighbourhood similarity could be ascribed to the continuous nature of the density measure which comprised all semantically related concepts given that they exceeded a similarity of greater than zero. Consequently, a large majority (98.17%; $SD = 2.62$; range: 84.83%–100%) of semantic neighbours

Fig. 3 Effect of close semantic neighbourhood density on naming latency (RT data was back-transformed to the original scale), naming accuracy (accurate versus inaccurate responses); semantic errors (coded as 1) versus accurate responses (coded as 0); coordinate errors (coded as 1) versus accurate responses (coded as 0); and omissions (coded as 1) versus accurate responses (coded as 0) depicted as linear regression line for naming

latency and logistic regression lines for accuracy and error responses with 95% confidence intervals. Points indicate average response times for naming latency or average number of accurate responses; semantic errors; coordinate errors; or omissions for each subject for three equal-sized bins of close semantic neighbourhood density

comprised a similarity of less than 0.5 and thus can be described as being semantically less similar (distant) to the target. For example, the target ‘Pfirsich’ (peach) has only ten semantically close neighbours that exceed a similarity of greater than 0.5 (e.g., nectarine, plum, melon), but it has 224 distant neighbours including ‘apple’, ‘potato’, and ‘ball’. While close semantic neighbours, such as ‘nectarine’ share many semantic features with the target (e.g., has a stone, is juicy, is soft, is circular/round, does grow, is edible), more distant neighbours share sometimes only a few or even one semantic feature(s). For example, ‘peach’ and ‘apple’ share the semantic features ‘is juicy’, ‘is circular/round’, ‘does grow’, and ‘is edible’, while ‘peach’ and ‘ball’ only share the semantic feature ‘is circular/round’.

In order to assess whether semantic neighbourhood density can affect naming performance if semantic neighbours exceed a certain degree of semantic similarity a more in-depth analysis of semantic neighbourhood density was run which included the variables close semantic neighbourhood density, distant semantic neighbourhood density and category-specific semantic neighbourhood density. The results of the semantic neighbourhood density analyses revealed significant interference effects of close semantic neighbourhood density on naming latency, accuracy, and naming errors. As predicted, naming difficulties increased with a target’s number of close

semantic neighbours leading to longer naming latencies, less accurate naming responses, and a higher likelihood of producing a semantic (coordinate) error or an omission over an accurate response. The significant effect of close semantic neighbourhood density and the absence of an influence of distant semantic neighbourhood density confirmed our assumption that semantic neighbourhood density can influence naming performance given semantic neighbours exceed a certain degree of semantic similarity.

The interfering effect of close semantic neighbourhood density replicates the results of Mirman (2011) in a different language (German instead of English), with a larger set of items from a different semantic database (Devereux et al., 2014). Moreover, we extended results of Mirman (2011) by finding evidence for an effect of close semantic neighbourhood density not only on naming accuracy and semantic errors but also on naming latency and omissions. The results are also compatible with the outcome of Rabovsky et al. (2016), who found similar effects of interference on naming latency and accuracy in picture naming for intercorrelational feature density. Intercorrelational feature density is a different measure of close semantic neighbourhood density which is based on an object’s proportion of feature pairs that co-occur together in other objects. “Objects with a greater proportion of co-occurring features

should have nearer neighbours because their features tend to come in groups (i.e., they co-occur), and thus their feature overlap will tend to be greater” (Mirman & Magnuson, 2008, p. 67; for more details, see McRae et al., 2005).

The nonsignificant results for category-specific neighbourhood density show that the influence of close semantic neighbourhood density cannot be explained by taxonomical relatedness only but instead can be ascribed to the number of semantically very similar (close) neighbours. The absence of a category-specific semantic neighbourhood density effect supports findings by Bormann (2011) which did not reveal a category-specific semantic neighbourhood density effect on naming latency and accuracy in a picture naming task with language unimpaired speakers.

How can our results contribute to the current debate about the underlying mechanism of lexical selection? The interfering influence of semantic neighbourhood similarity and close semantic neighbourhood density on naming performance confirmed the predictions of a competitive mechanism of lexical selection. According to most language-production theories, semantic neighbours become coactivated with the target through spreading activation between shared semantic information. In competitive theories, semantic neighbours modulate the ease of selection of the target’s lexical representation. One variant of lexical competition models, the swinging lexical network model by Abdel Rahman and Melinger (2009), was specifically designed to explain semantic neighbourhood effects. The model proposes that semantic neighbours simultaneously induce facilitation through priming at the conceptual level as well as interference through competition at the lexical level. Critically, the measurable net outcome of both effects depends on the number of semantic neighbours (i.e., semantic neighbourhood density) and their similarity (e.g., Rose & Abdel Rahman, 2017). For targets with many semantic neighbours and/or semantically very similar neighbours, lexical interference and therefore competition increases and can outweigh conceptual facilitation. The present study confirmed this prediction by revealing negative effects of semantic neighbourhood density on naming performance. However, a semantic neighbourhood density effect was only found for close, but not for the total number (raw), distant, or category-specific semantic neighbours, suggesting that the number of semantic neighbours require a sufficient degree of semantic similarity to the target in order to induce net interference. Furthermore, the influence of semantic neighbourhood similarity confirms that the more similar or closer semantic neighbours are to the target, the more highly they become coactivated, leading to stronger competition at the lexical level. As discussed in the introduction, possible ways to implement competition is in form of a Luce choice mechanism (e.g., Luce, 1959; Roelofs, 1992), or lateral inhibitory links between semantic neighbours at the lexical level (see Cutting & Ferreira, 1999; Harley, 1993a, 1993b; McClelland & Elman,

1986; McClelland & Rumelhart, 1981; Stemmer, 1985). Taken together, our results confirm the predictions made by models of competitive lexical selection and indicate that semantic neighbourhood density is at least partly modulated by semantic similarity. Activation resonates within the lexical-semantic network, that is, activation of the cohort (lexical and semantic representations of the target and its semantic neighbours) becomes stronger with an increasing number and semantic similarity of a target’s semantic neighbours, which results in more intense lexical competition.

As discussed earlier, noncompetitive models focus on context stimuli and account for interference effects by word distractors blocking the articulators (e.g., Mahon et al., 2007) or in the form of a weakening of previously coactivated but unnamed items (e.g., Oppenheim et al., 2010). These models are therefore agnostic with respect to the present findings because item-inherent variables that may influence lexical competition, rather than contexts, were manipulated. In the following we speculate how an implicit learning mechanism as suggested by Oppenheim et al. (2010) could account for our findings. Instead of competition during the process of lexical selection, Oppenheim et al. (2010) suggest that interference is caused by implicit learning induced by the selection of a lexical representation. Following the selection of a target word, connections between the coactivated representations at the conceptual and lexical level would be readjusted in order to make future retrieval of the target more efficient. In this scenario, the connections between semantic features and the lexical representation of the target would be strengthened to the extent that the target was ‘underactivated’ for sufficient selection, while the connections between the semantic features and the lexical representations of the target’s semantic neighbours would be weakened to the extent that they were ‘overactivated’. How could this account explain interference induced by item-inherent semantic neighbourhood density and similarity? Our speculation is that the present findings could only be explained if additional long-lasting or even hard-wired changes are assumed. If an item is named for the first time, a weakening of many closely related neighbours should not directly affect lexical selection. However, semantic neighbourhood density and distance might lead to more permanent adaptations of the connection weights between concepts and lexical representations and could thus result in generally slower and more error-prone naming of items in close and dense semantic neighbourhoods. Future research is needed to evaluate this speculation.

The immediate negative consequences for semantic neighbours after the retrieval of a target word have been referred to as cumulative semantic interference, whereby naming times increase linearly with the number of previously named categorically (e.g., Belke et al., 2005; Howard, Nickels, Coltheart, & Cole-Virtue, 2006) or associatively related targets (Rose & Abdel Rahman, 2017). Similar to semantic neighbourhood

effects, this phenomenon can be accounted for either by an implicit learning mechanism resulting in weakened activation of previously coactivated but unnamed items (Oppenheim et al., 2010) or by competitive lexical selection in combination with an implicit learning mechanism which strengthens activation levels of previously named items (Howard et al., 2006). In case of the former, lexical selection of the target leads to a weakening of the lexical-semantic connections of semantically related representations, such as the ones from members of the same semantic category. In case of the latter, lexical selection of the target leads to a strengthening of the link between the target's lexical-semantic representations turning the target into a stronger competitor in the next round of lexical processing. Given that our stimuli comprised several members of different semantic categories, we cannot rule out possible effects of cumulative semantic interference. This may interact with our similarity and density manipulations and result in slower naming latencies and/or lower naming accuracy for target words with many closely related conamed items compared to targets with fewer and/or less closely related conamed neighbours. For future studies, we would therefore suggest to control for effects of cumulative semantic interference by using the same number of category-specific (or semantically related) stimuli as targets.

Finally, what are the implications for word-finding difficulties in aphasia that can be derived from our study? Given the similarity between word-finding difficulties and errors produced by language unimpaired speakers in the speeded picture-naming task (e.g., Hodgson & Lambon Ralph, 2008; Kello, 2004; Kello & Plaut, 2010; Mirman, 2011) compared with individuals with aphasia with lexical and/or semantic impairment, semantic neighbourhood similarity and close semantic neighbourhood density are likely to be critical variables that can determine the ease of lexical selection, and thus successful word retrieval in aphasia. We would therefore suggest not only to control for both semantic neighbourhood variables in experimental studies but also to consider them for future assessment and treatment of language impairments. For example, the diagnosis of a language impairment at the lexical level is often based on semantic errors and/or omissions in picture naming in combination with an effect of lexical variables, such as frequency, with aphasic individuals showing more difficulties in naming pictures of low-frequency compared with high-frequency words. Given the lack of strength or even absence of a frequency effect in previous picture-naming studies (e.g., Carroll & White, 2007; Morrison, Ellis, & Quinlan, 1992; Nickels & Howard, 1995), semantic neighbourhood similarity and/or close semantic neighbourhood density might be more reliable variables for diagnostic purposes. Similarly, it might be sensible to structure the treatment of word-finding difficulties for aphasic individuals with semantic and/or lexical impairment hierarchically by considering semantic neighbourhood similarity and

the number of close semantic neighbours of treated words. Hence, individuals with aphasia could either start with the treatment of words with semantically less similar neighbours and/or fewer close semantic neighbours and systematically increase the level of difficulty by treating words with semantically more similar neighbours and/or many close semantic neighbours, or do it the other way around following the “complexity account of treatment efficiency” (e.g., Kiran & Thompson, 2003; Thompson, 2007).

Conclusion

The present study investigated how lexical selection in language production is influenced by semantic neighbourhood similarity (distance) and raw semantic neighbourhood density. Using a speeded picture-naming task, we found an effect of semantic neighbourhood similarity on naming accuracy and the produced error types. Naming pictures of targets with semantically more similar neighbours increased naming difficulties by leading to more naming errors, more specifically by increasing the likelihood of producing semantic errors and omissions over accurate responses. No main effect of raw semantic neighbourhood density and no interaction between raw semantic neighbourhood density and semantic neighbourhood similarity (distance) was found. We assessed further whether semantic neighbourhood density can affect naming performance if semantic neighbours exceed a certain degree of semantic similarity with three different density variables: The number of semantically close neighbours, the number of semantically distant neighbours, and the number of category-specific neighbours. The results showed a significant effect of close, but not of distant or category-specific semantic neighbourhood density. Naming pictures of targets with more close semantic neighbours led to longer naming latencies, less accurate responses, and an increased probability of producing semantic errors and omissions over accurate responses. The results show that word-inherent semantic attributes such as the similarity (distance) of semantic neighbours and the number of coactivated close semantic neighbours modulate lexical selection. These results support theories of lexical selection by competition but can probably also be accounted for by noncompetitive theories that incorporate competition in form of an implicit learning mechanism subsequent to lexical selection.

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Appendix A

Table 6 Target items including their semantic neighbourhood values

Items	SN-Similarity	SN-Density (raw)	SN-Density (close)	SN-Density (distant)	SN-Density (category specific)
Aal (eel)	0.11	305	1	304	29
Adler (eagle)	0.20	145	22	123	35
Affe (monkey)	0.09	238	0	238	53
Ameise (ant)	0.13	339	5	334	25
Ananas (pineapple)	0.15	193	3	190	24
Anker (anchor)	0.18	265	2	263	2
Apfel (apple)	0.18	221	15	206	24
Artischocke (artichoke)	0.23	183	15	168	28
Aubergine (aubergine)	0.11	270	1	269	28
Auto (car)	0.21	276	17	259	53
Avocado (avocado)	0.17	186	13	173	28
Ball (ball)	0.08	324	2	322	19
Banane (banana)	0.14	205	4	201	24
Bär (bear)	0.12	258	4	254	53
Besen (broom)	0.14	281	2	279	49
Bett (bed)	0.08	401	0	401	23
Biber (beaver)	0.09	260	0	260	53
Biene (bee)	0.11	333	3	330	25
Bikini (bikini)	0.10	256	3	253	48
Bluse (blouse)	0.21	91	6	85	48
Bohne (bean)	0.15	376	8	368	28
Bombe (bomb)	0.08	241	1	240	23
Boot (boat)	0.22	262	8	254	53
Brokkoli (broccoli)	0.19	183	19	164	28
Brot (bread)	0.09	228	0	228	102
Buch (book)	0.18	33	5	28	10
Bumerang (boomerang)	0.14	263	0	263	19
Bürste (brush)	0.15	223	2	221	49
Bus (bus)	0.17	321	18	303	53
Butter (butter)	0.10	167	1	166	102
Daumen (thumb)	0.06	106	2	104	12
Delphin (dolphin)	0.12	157	1	156	29
Donut (doughnut)	0.11	174	1	173	102
Drachen (kite)	0.07	390	0	390	19
Elch (moose)	0.14	247	4	243	53
Elefant (elephant)	0.09	265	0	265	53
Erbse (pea)	0.17	305	9	296	28
Esel (donkey)	0.12	190	0	190	53
Eule (owl)	0.11	186	3	183	35
Fähre (ferry)	0.17	290	8	282	53
Farn (fern)	0.25	114	15	99	25
Fenster (window)	0.10	297	0	297	3
Finger (finger)	0.07	137	2	135	12
Flamingo (flamingo)	0.16	190	3	187	35
Flasche (bottle)	0.13	183	2	181	16
Floß (raft)	0.16	239	4	235	53
Frisbee (Frisbee)	0.12	281	1	280	19
Frosch (frog)	0.11	310	3	307	8
Fuchs (fox)	0.12	252	0	252	53
Gans (goose)	0.13	355	25	330	35
Gewehr (rifle)	0.17	317	4	313	23
Gift (poison)	0.13	74	0	74	23
Giraffe (giraffe)	0.10	242	1	241	53
Glocke (bell)	0.20	303	4	299	24
Gorilla (gorilla)	0.12	257	2	255	53
Gurke (cucumber)	0.15	226	9	217	28
Gürtel (belt)	0.06	210	0	210	48
Hahn (cockerel)	0.12	207	8	199	35
Hai (shark)	0.11	267	6	261	29
Hamster (hamster)	0.15	264	6	258	53
Harfe (harp)	0.13	344	6	338	24
Helm (helmet)	0.14	310	3	307	48

Table 6 (continued)

Items	SN-Similarity	SN-Density (raw)	SN-Density (close)	SN-Density (distant)	SN-Density (category specific)
Hemd (shirt)	0.17	85	3	82	48
Herd (stove)	0.16	262	2	260	12
Hocker (stool)	0.16	450	6	444	23
Hose (trousers)	0.12	256	3	253	48
Huhn (chicken)	0.13	259	10	249	35
Hummer (lobster)	0.11	307	2	305	29
Hund (dog)	0.16	150	4	146	53
Hyäne (hyena)	0.15	165	1	164	53
Igel (hedgehog)	0.12	283	1	282	53
Jeans (jeans)	0.09	215	1	214	48
Käfer (beetle)	0.16	277	6	271	25
Käfig (cage)	0.15	344	0	344	16
Kalb (calf)	0.13	380	2	378	53
Kanu (canoe)	0.15	280	5	275	53
Kartoffel (potato)	0.10	304	3	301	28
Käse (cheese)	0.14	182	2	180	102
Katze (cat)	0.16	165	6	159	53
Ketchup (ketchup)	0.11	157	0	157	102
Kissen (cushion)	0.08	163	1	162	23
Klavier (piano)	0.14	358	8	350	24
Korb (basket)	0.13	272	2	270	16
Korken (cork)	0.06	318	0	318	33
Kran (crane)	0.17	331	0	331	53
Kröte (toad)	0.14	251	2	249	8
Kuchen (cake)	0.13	189	1	188	102
Kuh (cow)	0.09	366	1	365	53
Kutsche (carriage)	0.13	261	4	257	53
Lama (llama)	0.12	294	1	293	53
Lamm (lamb)	0.12	357	2	355	53
Lampe (lamp)	0.08	257	0	257	23
Laterne (lantern)	0.14	308	0	308	33
Libelle (dragonfly)	0.11	312	8	304	25
Lineal (ruler)	0.17	332	0	332	49
Löwe (lion)	0.09	337	1	336	53
Mais (corn)	0.13	175	2	173	28
Mango (mango)	0.15	225	10	215	24
Mantel (coat)	0.13	169	8	161	48
Marmelade (jam)	0.11	178	0	178	102
Maus (mouse)	0.16	284	7	277	53
Mehl (flour)	0.08	160	0	160	102
Mücke (mosquito)	0.10	287	2	285	25
Münze (coin)	0.17	363	0	363	0
Murmel (marble)	0.10	283	0	283	19
Muschel (clam)	0.06	262	10	252	29
Nagel (nail)	0.15	421	13	408	49
Orgel (organ)	0.14	317	3	314	24
Petersilie (parsley)	0.18	205	14	191	28
Pfau (peacock)	0.10	243	2	241	35
Pfeil (arrow)	0.16	371	5	366	23
Pferd (horse)	0.11	275	1	274	53
Pfirsich (peach)	0.13	234	10	224	24
Pflaume (plum)	0.11	281	5	276	24
Pinguin (penguin)	0.13	209	1	208	35
Pinzette (tweezers)	0.18	354	7	347	49
Pistole (gun)	0.18	257	5	252	23
Pyramide (pyramid)	0.04	178	0	178	2
Qualle (jellyfish)	0.09	155	0	155	29
Rabe (raven)	0.16	257	25	232	35
Radio (radio)	0.15	273	0	273	12
Rakete (rocket)	0.17	332	1	331	53
Rasierer (razor)	0.20	275	15	260	49
Ratte (rat)	0.11	246	3	243	53
Reh (deer)	0.12	207	1	206	53
Reifen (tyre)	0.10	147	1	146	2
Reis (rice)	0.11	337	1	336	0

Table 6 (continued)

Items	SN-Similarity	SN-Density (raw)	SN-Density (close)	SN-Density (distant)	SN-Density (category specific)
Robbe (seal)	0.10	225	2	223	53
Rose (rose)	0.12	194	10	184	25
Rosine (raisin)	0.11	313	4	309	102
Salat (lettuce)	0.19	167	12	155	28
Sarg (coffin)	0.13	310	0	310	17
Schaf (sheep)	0.09	297	1	296	53
Schal (scarf)	0.13	181	6	175	48
Schaukel (swing)	0.16	286	0	286	19
Schinken (ham)	0.10	181	1	180	102
Schleier (veil)	0.12	188	2	186	48
Schlitten (sledge)	0.15	302	1	301	19
Schmetterling (butterfly)	0.14	197	3	194	25
Schnecke (snail)	0.07	304	3	301	25
Schokolade (chocolate)	0.12	217	0	217	102
Schuh (shoe)	0.08	236	2	234	48
Schwan (swan)	0.14	209	5	204	35
Schwein (pig)	0.09	264	0	264	53
Sellerie (celery)	0.15	242	15	227	28
Ski (ski)	0.12	309	1	308	19
Skorpion (scorpion)	0.12	311	0	311	25
Spargel (asparagus)	0.16	265	18	247	28
Spiegel (mirror)	0.07	255	0	255	23
Spritze (syringe)	0.17	270	0	270	49
Stein (stone)	0.09	266	1	265	1
Stiefel (boot)	0.09	166	2	164	48
Tanne (fir)	0.12	300	8	292	25
Tasse (cup)	0.10	341	4	337	33
Taxi (taxi)	0.13	335	1	334	53
Telefon (telephone)	0.10	183	0	183	12
Teller (plate)	0.11	306	1	305	33
Thron (throne)	0.11	395	0	395	23
Tiger (tiger)	0.10	328	1	327	53
Tisch (table)	0.15	449	4	445	23
Tomate (tomato)	0.12	332	8	324	28
Tor (gate)	0.25	159	5	154	3
Traktor (tractor)	0.13	302	2	300	53
Trompete (trumpet)	0.16	250	7	243	24
Tulpe (tulip)	0.15	154	10	144	25
Wal (whale)	0.15	222	5	217	29
Wiege (cradle)	0.10	339	1	338	23
Wolf (wolf)	0.11	208	1	207	53
Würfel (dice)	0.08	431	0	431	19
Wurm (worm)	0.07	380	1	379	25
Zaun (fence)	0.22	306	11	295	3
Zeh (toe)	0.09	193	2	191	12
Zeitung (newspaper)	0.07	173	4	169	10
Ziege (goat)	0.11	147	2	145	53
Zigarette (cigarette)	0.07	214	2	212	11
Zigarre (cigar)	0.05	237	2	235	11
Zitrone (lemon)	0.09	298	5	293	24
Zucker (sugar)	0.11	222	0	222	102
Zunge (tongue)	0.05	140	0	140	12
Zwiebel (onion)	0.11	295	0	295	28

Appendix B

Table 7 Summary of the range, mean, and standard deviation of the different psycholinguistic variables ($n = 180$ items)

Variables	Range	Mean	<i>SD</i>
Semantic neighbourhood similarity	0.04–0.25	0.13	0.04
Semantic neighbourhood density (raw)	33–450	255.54	75.18
Semantic neighbourhood density (close)	0–25	4.04	5.01
Semantic neighbourhood density (distant)	28–445	251.49	75.55
Semantic neighbourhood density (category specific)	0–102	37.08	23.19
Semantic richness	6–30	17.03	3.99
Imageability	3.3–7.0	6.06	0.66
Typicality	1.0–6.1	2.88	1.22
Concept familiarity	1.6–5.0	3.27	0.9
Age of acquisition	1.0–5.0	2.31	0.83
Visual complexity	1.4–4.8	2.91	0.65
Lemma frequency	0–4.43	2.81	0.69
Length (number of phonemes)	2–9	4.64	1.49

Appendix C

Table 8 A list of the different error responses including their error type

Target item	Error response	Error type
Aal (eel)	<i>Schlange (snake)</i>	Semantic
Adler (eagle)	<i>Falke (falcon); Geier (vulture); Vogel (bird)</i>	Semantic
Ameise (ant)	<i>Spinne (spider); Hühner (chicken)</i>	Semantic
Artischocke (artichoke)	<i>Avocado (avocado); Kohl (cabbage)</i>	Semantic
Aubergine (aubergine)	<i>Avocado (avocado); Artischocke (artichoke); Zucc(hini)* (zucchini)</i>	Semantic
Avocado (avocado)	<i>Aubergine (aubergine)</i>	Semantic
Biber (beaver)	<i>Hamster (hamster); Otter (otter); Ratte (rat); Waschbär (raccoon)</i>	Semantic
Biene (bee)	<i>Wespe (wasp)</i>	Semantic
Bluse (blouse)	<i>Jacke (jacket); Hemd (shirt)</i>	Semantic
Bohne (bean)	<i>Erbse (pea); Schote (pod)</i>	Semantic
Bombe (bomb)	<i>Dynamit (dynamite)</i>	Semantic
Boot (boat)	<i>Kanu (canoe); Ruderboot (rowboat); Schiff (ship)</i>	Semantic
Brokkoli (broccoli)	<i>Kohlrabi (kohlrabi or cabbage turnip)</i>	Semantic
Bumerang (boomerang)	<i>Bogen (bow); Frisbee (Frisbee)</i>	Semantic
Bürste (brush)	<i>Besen (broom); Schwamm (sponge)</i>	Semantic
Butter (butter)	<i>Käse (cheese)</i>	Semantic
Daumen (thumb)	<i>Finger (finger); Hand (hand)</i>	Semantic
Delphin (dolphin)	<i>Hai (shark); Wal (whale)</i>	Semantic
Donut (doughnut)	<i>Muffin (muffin)</i>	Semantic
Elch (moose)	<i>Hirsch (deer); Hirschkuh (hind)</i>	Semantic
Erbse (pea)	<i>Bohne (bean)</i>	Semantic
Esel (donkey)	<i>Pferd (horse); Zebra (zebra)</i>	Semantic
Eule (owl)	<i>Taube (pigeon); Vogel (bird)</i>	Semantic
Fähre (ferry)	<i>Boot (boat); Dampfer (steamship); Schiff (ship); Auto (car)</i>	Semantic
Farn (fern)	<i>Kraut (herb); Pflanze (plant)</i>	Semantic
Fenster (window)	<i>Tür (door)</i>	Semantic
Flamingo (flamingo)	<i>Pelikan (pelican); Pinguin (penguin); Strauß)* (ostrich); Vogel (bird)</i>	Semantic
Flasche (bottle)	<i>Glas (glass); Wasser (water)</i>	Semantic
Floß (raft)	<i>Boot (boat); Hausboot (houseboat); Schiff (ship)</i>	Semantic
Frosch (frog)	<i>Kröte (toad)</i>	Semantic
Gans (goose)	<i>Huhn (chicken); Ente (duck); Schwan (swan)</i>	Semantic
Gewehr (rifle)	<i>Knarre (gun); Pistole (gun); Waffe (weapon)</i>	Semantic
Gift (poison)	<i>giftig (poisonous); Flasche (bottle)</i>	Semantic
Glocke (bell)	<i>Klingel (doorbell)</i>	Semantic
Gorilla (gorilla)	<i>Affe (monkey); Bär (bear); Orang-Utan (orangutan)</i>	Semantic

Table 8 (continued)

Target item	Error response	Error type
Hahn (cockerel)	<i>Huhn (chicken); Henne (chicken)</i>	Semantic
Hai (shark)	<i>Wal (whale)</i>	Semantic
Hamster (hamster)	<i>Maus (mouse)</i>	Semantic
Hemd (shirt)	<i>T-Shirt (T-shirt)</i>	Semantic
Herd (stove)	<i>Ofen (oven)</i>	Semantic
Hocker (stool)	<i>Stuhl (chair); Tisch (table)</i>	Semantic
Huhn (chicken)	<i>Hahn (cockerel)</i>	Semantic
Hummer (lobster)	<i>Krabbe (crab); Krebs (crayfish)</i>	Semantic
Hyäne (hyena)	<i>Gepard (cheetah); Kojote (coyote); Tier (animal)</i>	Semantic
Käfer (beetle)	<i>Spinne (spider)</i>	Semantic
Käfig (cage)	<i>Korb (basket); Gitter (grid)</i>	Semantic
Kalb (calf)	<i>Lamm (lamb); Ziege (goat)</i>	Semantic
Kanu (canoe)	<i>Boot (boat)</i>	Semantic
Kartoffel (potato)	<i>Karotte (carrot)</i>	Semantic
Käse (cheese)	<i>Essen (food)</i>	Semantic
Kran (crane)	<i>Bagger (digger)</i>	Semantic
Kröte (toad)	<i>Frosch (frog)</i>	Semantic
Kutsche (carriage)	<i>Wagen (wagon)</i>	Semantic
Lama (llama)	<i>Schaf (sheep); Ziege (goat)</i>	Semantic
Lamm (lamb)	<i>Kalb (calf); Ziege (goat)</i>	Semantic
Laterne (lantern)	<i>Lampe (lamp)</i>	Semantic
Libelle (dragonfly)	<i>Biene (bee); Fliege (fly); Floh (flea); Mücke (mosquito)</i>	Semantic
Lineal (ruler)	<i>Maßband (measuring tape); Messgerät (measuring instrument)</i>	Semantic
Löwe (lion)	<i>Tiger (tiger)</i>	Semantic
Mais (corn)	<i>Kohlrabi (kohlrabi or cabbage turnip); Kür(bis)* (pumpkin)</i>	Semantic
Mango (mango)	<i>Ananas (pineapple); Avocado (avocado)</i>	Semantic
Mantel (coat)	<i>Jacke (jacket)</i>	Semantic
Marmelade (jam)	<i>Glás (jar)</i>	Semantic
Maus (mouse)	<i>Ratte (rat)</i>	Semantic
Mücke (mosquito)	<i>Biene (bee); Fliege (fly); Insekt (insect); Spin(ne)* (spider);</i>	Semantic
Murmel (marble)	<i>Ball (ball); Kugel (ball)</i>	Semantic
Muschel (clam)	<i>Schneck(e) (snail)</i>	Semantic
Nagel (nail)	<i>Hammer (hammer); Nadel (needle)</i>	Semantic
Orgel (organ)	<i>Klavier (piano)</i>	Semantic
Petersilie (parsley)	<i>Gemüse (vegetable); Radies(chen)* (radish); Schnittlauch (chive); Sellerie (celery); grün (green)</i>	Semantic
Pfau (peacock)	<i>Strauß (ostrich); Pelikan (pelican); Vogel (bird)</i>	Semantic
Pfeil (arrow)	<i>Speer (spear)</i>	Semantic
Pfirsich (peach)	<i>Apfel (apple); Apfelsine (orange); Aprikose (apricot); Nektarine (nectarine)</i>	Semantic
Pflaume (plum)	<i>Kirsche (cherry)</i>	Semantic
Pinguin (penguin)	<i>Sper(ling)* (sparrow)</i>	Semantic
Pinzette (tweezers)	<i>Zange (pliers)</i>	Semantic
Pistole (gun)	<i>Gewehr (rifle); Kanone (cannon); Waffe (weapon)</i>	Semantic
Pyramide (pyramid)	<i>Wüste (desert)</i>	Semantic
Rabe (raven)	<i>Amsel (blackbird); Krähe (crow); Taube (pigeon); Vogel (bird)</i>	Semantic
Rasierer (razor)	<i>Rasierklinge (razor blade)</i>	Semantic
Ratte (rat)	<i>Maus (mouse)</i>	Semantic
Reh (deer)	<i>Bambi (Bambi); Elch (moose); Hirsch (stag)</i>	Semantic
Reifen (tyre)	<i>Rad (wheel)</i>	Semantic
Robbe (seal)	<i>Wal (whale)</i>	Semantic
Salat (lettuce)	<i>Kohl (cabbage); Kohlrabi (kohlrabi or cabbage turnip)</i>	Semantic
Sarg (coffin)	<i>Kiste (box or case); Truhe (chest)</i>	Semantic
Schinken (ham)	<i>Fleisch (meat); Wurst (sausage)</i>	Semantic
Schleier (veil)	<i>Hochzeit (wedding); Braut (bride)</i>	Semantic
Schwan (swan)	<i>Gan(s)* (goose)</i>	Semantic
Sellerie (celery)	<i>Fenchel (fennel); Gemüse (vegetable); Lauch (leek); Lauchzwiebel (spring onion)</i>	Semantic
Ski (ski)	<i>Snowboard (snowboard)</i>	Semantic
Skorpion (scorpion)	<i>Hummer (lobster); Krebs (crayfish)</i>	Semantic
Spritze (syringe)	<i>Pinzette (tweezers); Nadel (needle)</i>	Semantic
Stiefel (boot)	<i>Schuh (shoe)</i>	Semantic
Tanne (fir)	<i>Baum (tree); Weihnachtsbaum (Christmas tree)</i>	Semantic
Tasse (cup)	<i>Becher (beaker)</i>	Semantic
Taxi (taxi)	<i>Auto (car)</i>	Semantic
Thron (throne)	<i>Stuhl (chair); Sessel (armchair)</i>	Semantic
Tiger (tiger)	<i>Lö(we)* (lion); Jagu(ar)* (jaguar)</i>	Semantic
Tisch (table)	<i>Stuhl(l)* (chair)</i>	Semantic

Table 8 (continued)

Target item	Error response	Error type
Tomate (tomato)	<i>Kirsche (cherry); Avo(cado) (avocado)</i>	Semantic
Tor (gate)	Gitter (grid); Zaun (fence)	Semantic
Traktor (tractor)	Auto (car); Bagger (digger)	Semantic
Tulpe (tulip)	Blume (flower); Rose (rose)	Semantic
Wiege (cradle)	Bett (bed); Schau(kel)* (swing)	Semantic
Wolf (wolf)	Fuchs (fox); Hund (dog); Hyäne (hyaena)	Semantic
Wurm (worm)	Schlange (snake)	Semantic
Zaun (fence)	Gatter (gate); Gitter (grid)	Semantic
Zeh (toe)	Fuß (foot); Nagel (nail)	Semantic
Ziege (goat)	Lama (llama); Reh (deer); Scha(f)* (sheep)	Semantic
Zigarre (cigar)	Zigarette (cigarette); Zigarillo (cigarillo)	Semantic
Zitrone (lemon)	Orange (orange); Zwiebel (onion)	Semantic
Zucker (sugar)	Salz (salt)	Semantic
Affe (monkey)	/halk/	Other
Ananas (pineapple)	/ana:/	Other
Anker (anchor)	/ank/; /kank/	Other
Aubergine (aubergine)	/o:b/	Other
Avocado (avocado)	/avo:/	Other
Banane (banana)	/na:n /; /a:n /	Other
Bär (bear)	/ba:r/	Other
Biene (bee)	/bi:/	Other
Brokkoli (broccoli)	/br /	Other
Bürste (brush)	Fön (hair dryer)	Other
Drachen (kite)	/i:ga/	Other
Elefant (elephant)	/fant/	Other
Eule (owl)	/ m/; Öl (oil)	Other
Fähre (ferry)	/ r /	Other
Flasche (bottle)	/ py l/	Other
Floß (raft)	/flo:/	Other
Frisbee (frisbee)	Scheibe (disc)	Other
Gans (goose)	/fe:/	Other
Gift (poison)	Alkohol (alcohol); Schnaps (hard liquor); Wodka (vodka); Sekt (sparkling wine)	Other
Glocke (bell)	/k /	Other
Gorilla (gorilla)	/aslo:/; /i:l/	Other
Hahn (cockerel)	/ e:/	Other
Harfe	/harp /; / b/	Other
Hyäne (hyena)	/hy /	Other
Käfer (beetle)	/sɛ/	Other
Ketchup	Staubsauger (vacuum cleaner)	Other
Korb (basket)	/ba:/	Other
Kutsche (carriage)	Shop	Other
Marmelade (jam)	/la:d /	Other
Maus (mouse)	/ma:/	Other
Murmel (marble)	/m r/	Other
Nagel (nail)	Pfeil (arrow)	Other
Pfau (peacock)	/ ɛ/	Other
Pinguin (penguin)	/gui:n/	Other
Rabe (raven)	/rea:/	Other
Rosine (raisin)	/ro:/	Other
Sarg (coffin)	/ro:/	Other
Sellerie (celery)	/sɛ/	Other
Skorpion (scorpion)	/le:/	Other
Spargel (asparagus)	/ pa:/	Other
Thron (throne)	/ ɛtro:n/	Other
Tisch (table)	/ pe:/	Other
Tor (gate)	/ke:/	Other
Wiege (cradle)	Krippe (cratch)	Other
Wurm (worm)	Amme (wet nurse)	Other
Zeh (toe)	/ e:/	Other
Zeitung (newspaper)	/tsi:t/	Other
Zigarette (cigarette)	/arɛt /; Holz (wood); / i: a arɛt /	Other
Zucker (sugar)	/tsa /	Other

Semantic coordinate errors are printed in italic; semantically related false starts are highlighted by a *

Appendix D

Table 9 Bivariate correlations (Pearson's r) between the different measures of semantic neighbourhood and other psycholinguistic variables

	SN-Density (raw)	SN-Density (close)	SN-Density (distant)	SN-Density (category)	Semantic richness	Imageability	Semantic typicality	Familiarity	AoA	Lemma frequency	Visual complexity	Length
SN-Similarity	-0.051	0.556	-0.088	-0.058	-0.244	-0.014	0.121	-0.102	0.144	-0.131	0.042	0.028
SN-Density (raw)		-0.037	0.998	-0.145	0.115	.297	-0.023	-0.134	-0.058	0.021	-0.06	-0.079
SN-Density (close)			-0.103	-0.107	-0.086	0.032	-0.083	0.062	0.083	-0.115	-0.064	0.029
SN-Density (distant)				-0.137	0.12	0.293	-0.018	-0.137	-0.063	0.028	-0.055	-0.081
SN-Density (category)					0.201	-0.076	0.078	0.029	-0.072	-0.131	0.097	-0.039
Semantic richness						0.058	-0.368	-0.1	-0.254	0.129	0.232	-0.081
Imageability							-0.027	-0.07	-0.089	-0.029	0.096	0.008
Semantic Typicality								-0.374	.673	-.471	.198	.197
Familiarity									-.465	.287	-.492	0.002
AoA										-.553	.178	.302
Lemma frequency											-0.026	-.297
Visual complexity												-0.065

Significant correlations are highlighted in bold

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