Similarity-based interference in sentence comprehension in aphasia: A computational
evaluation of two models of cue-based retrieval

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Abstract

Sentence comprehension requires the listener to link incoming words with short-term memory representations in order to build linguistic dependencies. The cue-based retrieval theory of sentence processing predicts that the retrieval of these memory representations is affected by similarity-based interference. We present the first large-scale computational evaluation of interference effects in two models of sentence processing – the activation-based model, and a modification of the direct-access model – in individuals with aphasia (IWA) and control participants in German. The parameters of the models are linked to prominent theories of processing deficits in aphasia, and the models are tested against two linguistic constructions in German: Pronoun resolution and relative clauses. The data come from a visual-world eye-tracking experiment combined with a sentence-picture matching task. The results show that both control participants and IWA are susceptible to retrieval interference, and that a combination of theoretical explanations (intermittent deficiencies, slow syntax, and resource reduction) can explain IWA’s deficits in sentence processing. Model comparisons reveal that both models have a similar predictive performance in pronoun resolution, but the activation-based model outperforms the direct-access model in relative clauses.

Keywords: computational modeling, cue-based retrieval, sentence comprehension, aphasia, cognitive modeling

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Introduction

When hearing a sentence, the listener has to link incoming words together and build up syntactic and semantic relations in real time. For instance, verbs have to be linked with their dependent arguments, which is commonly assumed to require retrieval from memory (Lewis, 1999; McElree, 2006; Van Dyke & Lewis, 2003). In a sentence like (1), when the verb *greeted* is reached, the comprehender must retrieve the subject *boy* from memory in order to understand who greeted whom. In linguistics, resolving who did what to whom is known as thematic role assignment. The doer of the action expressed by the verb is the agent (*boy*) and the recipient of the action is the theme (*girl*).

- (1) The boy who greeted the girl plays with the dog.

The cue-based retrieval theory (Lewis & Vasishth, 2005; Lewis, Vasishth, & Van Dyke, 2006; McElree, 2000; McElree, Foraker, & Dyer, 2003; Vasishth, Nicenboim, Engelmann, & Burchert, 2019) posits that items are retrieved from memory based on their syntactic and semantic features.¹ According to cue-based retrieval as implemented computationally in Lewis and Vasishth (2005), items are stored in memory as a bundle of feature-value pairs. In a subject relative clause such as (1), the verb *greeted* triggers the retrieval of an item in memory whose features match the retrieval cues [+animate] and [+agent]. When *greeted* is read, the only item in memory that matches these retrieval cues is *boy*. Consider now sentence (2), which is an object relative clause.

- (2) The girl who the boy greeted plays with the dog.

¹ Following Parker, Shvartsman, and Van Dyke (2017), we refer to all the different types of cue-based retrieval accounts as “the” cue-based retrieval theory, even though there are important differences in the underlying latent process assumed and the quantitative predictions of the different variants (e.g., Lissón et al., 2021a; Nicenboim & Vasishth, 2018).

In this case, when the comprehender reaches the verb *greeted*, there is one item in memory that matches all the retrieval cues set by the verb, *boy*, but there is also another item that matches some of the retrieval cues, *girl* ([+animate, -agent]). Following Jäger, Engelmann, and Vasishth (2017), we will refer to the fully-matching item (*boy*) as the retrieval target, and to items with partial feature match (*girl*) as distractors.

A core assumption of the cue-based retrieval theory is that memory retrieval is subject to interference: When a retrieval is triggered, processing difficulty is predicted if multiple items in memory match the same retrieval cues. Therefore, the verb *greeted* should be more difficult to process in (2) than in (1). This effect is known as similarity-based interference, and is indexed by a slowdown at the retrieval site and/or by the occasional misretrieval of a distractor item, which results in misinterpretation. Similarity-based interference has been attested in multiple linguistic constructions across different languages (e.g., Engelmann, Jäger, & Vasishth, 2019; Jäger et al., 2017; Jäger, Mertzen, Van Dyke, & Vasishth, 2020; A. E. Martin, Nieuwland, & Carreiras, 2012; Van Dyke, 2007; Van Dyke & Lewis, 2003; Van Dyke & McElree, 2006, 2011; Vasishth, Brüssow, Lewis, & Drenhaus, 2008; Vasishth & Engelmann, 2022).

Within the cue-based retrieval framework, two different models of retrieval processes have been proposed: The activation-based model (Lewis & Vasishth, 2005), and the direct-access model (McElree, 2000). The two models share the assumption that retrieval cues mediate access to items in memory. However, they make different assumptions regarding the underlying latent processes that unfold in memory retrieval.

The activation-based model was originally implemented in the cognitive architecture ACT-R (Anderson et al., 2004). Because the full ACT-R based model is implemented in the programming language Lisp, it is not easily accessible to the wider community in psycholinguistics. Partly in response to this problem, Engelmann et al. (2019) developed an implementation in R (R Core Team, 2020) that represents a simplified version of the full

model.² The match between simulated data from the Lewis and Vasishth (2005) model and human experimental data has been studied in subject-verb and reflexive-antecedent dependencies, negative polarity items, and other linguistic constructions (Dillon, Mishler, Sloggett, & Phillips, 2013; Jäger, Engelmann, & Vasishth, 2015; Jäger et al., 2020; Nicenboim & Vasishth, 2016; Parker & Phillips, 2017; Patil, Vasishth, & Lewis, 2016; Vasishth & Lewis, 2006; Vasishth et al., 2019; Wagers, Lau, & Phillips, 2009, *inter alia*).

In the activation-based model implemented in Lewis and Vasishth (2005), each memory item has a fluctuating activation value that determines both the probability and the latency of retrieval. When a retrieval is triggered, the retrieval cues spread activation to all matching items available in memory. Items with more matches accrue more activation, making them more likely to be retrieved, and decreasing retrieval speed. If the cued feature is present on multiple items in memory, the cue’s activation is shared across all items, so that each item receives comparatively less activation. The reduced activation of items in memory leads to difficulty in retrieving the correct item; this is a key property of similarity-based interference.

The direct-access model, developed by McElree and colleagues (A. E. Martin & McElree, 2011; McElree, 2000, 2006; McElree et al., 2003) also predicts similarity-based interference. It assumes that the availability of items in memory – that is, the probability of successful retrieval – decreases as a function of interference, but that retrieval times remain unaffected. However, low availability can lead to misretrievals and/or a parsing failure. When an initial misretrieval occurs, in a certain proportion of trials, a backtracking process is initiated. Backtracking, also known as reanalysis, is implicitly assumed to lead to the retrieval of the target (McElree, 1993). Backtracking requires some extra processing time that is independent of the retrieval time (A. E. Martin & McElree, 2008).

The assumption that backtracking leads to the retrieval of the target constrains the

² A Shiny app provides easy access to this simplified model’s quantitative predictions under parametric variation: <https://vasishth.github.io/RetrievalModels/>

direct-access model: Due to the added backtracking time in some trials, the direct-access model assumes that final correct retrievals are, on average, slower than misretrievals. However, it is known from different cognitive tasks that “slow errors” can occur in addition to “fast errors” (e.g., van Maanen, Katsimpokis, and van Campen, 2019). In addition, the direct-access model’s assumption that correct retrievals are on average slower than incorrect retrievals leads to incorrect predictions when modeling data from individuals with aphasia with the direct-access model (Lissón et al., 2021a). The reason is that individuals with aphasia often have slower latencies in incorrect trials relative to correct trials (see Adelt, Stadie, Lassotta, Adani, & Burchert, 2017; Hanne, Burchert, de Bleser, & Vasishth, 2015; Pregla, Lissón, Vasishth, Burchert, & Stadie, 2021). Lissón et al. (2021b) implemented a modified version of the direct-access model in which backtracking can fail, resulting in a misretrieval. Lissón et al. (2021b) tested the modified direct-access model and the original direct-access model against self-paced listening data from individuals with aphasia (IWA) and control participants in German (Pregla et al., 2021). The models were compared using Bayes factors, and the result was inconclusive. The authors concluded that more studies testing the modified direct-access model in IWA are needed, in order to evaluate the fit of the modified-direct access model to data from IWA and controls. In the present study, we follow Lissón et al. (2021b) and implement a modified direct-access model in which backtracking can fail, resulting in slowed reaction times and a misretrieval. In the modified direct-access model, both correct and incorrect responses are therefore a mixture of directly-accessed and backtracked retrievals. In the present work we focus on evaluating the modified direct-access model, but for the sake of completeness, we also report model comparisons between the modified and the original direct-access model, i.e., a model in which backtracking can only lead to the retrieval of the target.

Nicenboim and Vasishth (2018) were the first to implement activation-based and the direct-access models in a Bayesian framework. The authors modeled a large self-paced reading dataset that investigated similarity-based interference in unimpaired adult readers

(Nicenboim, Vasishth, Engelmann, & Suckow, 2018). Nicenboim and Vasishth (2018) showed that the predictive performance of the default activation-based model implementation was worse compared to that of the direct-access model. However, the models had similar quantitative performance when the activation-based model was implemented with different variances for target and distractors. Lissón et al. (2021a) tested the two competing models against self-paced listening data from individuals with aphasia and control participants (Caplan, Michaud, & Hufford, 2015). The authors modeled the comprehension of English subject and object relative clauses as in (1) and (2), in self-paced listening and a sentence-picture matching task. Model comparisons showed similar quantitative performance, but major qualitative differences. Lissón et al. concluded that in order to disentangle the differences between the models, more studies using different linguistic constructions and different experimental paradigms were needed. This is the empirical gap that the current study aims to fill.

We model interference effects in IWA and control participants using a subset of the data from Pregla, Vasishth, Lissón, Stadie, and Burchert (2022). We focus on two linguistic constructions in German: Pronoun resolution and relative clauses. These constructions are well-suited for our modeling goals because IWA have been found to have comprehension difficulties processing them (Adelt et al., 2017; Burchert, de Bleser, & Sonntag, 2003; Caplan et al., 2015; Choy & Thompson, 2010; Pregla et al., 2021). Because we map prominent theories of processing deficits in aphasia to the different parameters of each model, we expect to gain valuable insights into the nature of comprehension deficits in IWA by investigating how the two competing models of retrieval fit these constructions. In addition, we simultaneously model reaction times and accuracies from a sentence-picture matching task, as well as visual-world eye-tracking data. This is a novel approach that allows for the simultaneous assessment of IWA’s online and offline comprehension within the same model. Our study is, to our knowledge, the first to compare two different models of cue-based retrieval using the visual-world paradigm and behavioral data from both IWA

and unimpaired controls.³

We seek to answer the following questions: 1) Which model offers a better account of interference effects in IWA and control participants in pronoun resolution and in relative clauses? 2) What do the parameters of each model tell us about the source of processing deficits and interference in IWA?

We begin by summarizing the theories of processing deficits in aphasia that we will evaluate, as well as their proposed connection to the parameters of the activation-based and modified direct-access models.

Theories of processing deficits in aphasia

Individuals with aphasia have difficulties processing non-canonical sentences (e.g., Caramazza and Zurif, 1976; McAllister, Bachrach, Waters, Michaud, and Caplan, 2009; Schumacher et al., 2015) such as object relative clauses and passives, especially when the thematic roles are semantically reversible. That is, IWA experience difficulties identifying the agent and theme of the verb (who did what to whom) based on morpho-syntactic cues alone. Similarly, IWA also experience difficulties comprehending binding relations, i.e., pronouns and reflexives (e.g., *Justin told [Thomas_i to shave himself_i]*; Choy and Thompson, 2010; Edwards and Varlokosta, 2007).

Caplan et al. (2015) discuss the different theories that aim to explain why these constructions are challenging for IWA⁴. For instance, Burkhardt, Piñango, and Wong (2003) and Burkhardt, Avrutin, Piñango, and Ruigendijk (2008) argue that IWA compute syntactic dependencies at a slower-than-normal pace, which can lead to comprehension

³ Patil, Hanne, Burchert, de Bleser, and Vasishth (2016) modeled visual-world eye-tracking data from 7 IWA and 8 controls with different versions of the Lewis and Vasishth (2005) model, but the (modified) direct-access model has never been tested against visual-world eye-tracking data, and never with such a relatively large-scale dataset from IWA and controls.

⁴ Although the slow syntax and the delayed lexical access theories were originally proposed for Broca's aphasia, the studies by Caplan and colleagues (Caplan, Michaud, & Hufford, 2013, 2015) show that these deficits could also be playing an important role in impaired sentence comprehension in patients with other types of aphasia.

failure. According to this theory, known as *slow syntax*, the processing deficit in IWA is specific to syntactic structure building. By contrast, Ferrill, Love, Walenski, and Shapiro (2012), Love, Swinney, Walenski, and Zurif (2008) posit that *delayed lexical access* causes the slowdown in the formation of syntactic dependencies. Love et al. claim that when the sentence requires the reactivation of a lexical item in order to complete a dependency, the lexical reactivation is too slow, and an extragrammatical heuristic may be used instead, which can lead to comprehension errors. These two theories –slow syntax and delayed lexical access– have been tested using the cross-modal lexical decision paradigm. However, studies using the visual-world paradigm in aphasia do not support a delay in lexical access or in syntactic structure building as the main source of comprehension deficits in IWA (e.g., Dickey, Choy, & Thompson, 2007). The data modeled in the present work is well-suited to test the predictions of these two theories, because we consider visual-world data, as well as reaction times and accuracies from a picture selection task, which require similar motor responses as in the cross-modal lexical decision task.

Another theory, proposed by Caplan and colleagues, argues that IWA may have an impairment in the resources needed for parsing, such as memory capacity (Caplan, 2012; Caplan, Waters, DeDe, Michaud, & Reddy, 2007). Complex sentences create greater processing demands, and therefore IWA have more difficulties in complex sentences. This account is known as *resource reduction*.

In addition, Caplan et al. (2013) claim that IWA may also exhibit *intermittent deficiencies* in the parsing system that block access to parsing operations such as relating the surface and base positions of words in the structure. The intermittent nature of these breakdowns would explain why IWA are able to understand complex sentences on some but not all trials.

All of these theoretical proposals can be incorporated in computational models of retrieval. For instance, Patil, Hanne, et al. (2016) modeled the comprehension of active vs. passive sentences in a visual-world eye-tracking experiment in German (Hanne, Sekerina,

Vasishth, Burchert, & de Bleser, 2011). Patil and colleagues implemented different versions of Lewis and Vasishth (2005). The model that provided a better fit for IWA assumed a slowed processing deficit (understood as a combination of delayed lexical access and slow syntax), and intermittent deficiencies. Mätzig, Vasishth, Engelmann, Caplan, and Burchert (2018) mapped parameters of the Lewis and Vasishth (2005) model to slow processing (understood as a combination of delayed lexical access and slow syntax), intermittent deficiencies, and resource reduction. The authors modeled accuracies in English subject and object relative clauses using the data from Caplan et al. (2015). They concluded that IWA’s performance can be explained by a combination of these three deficits, and that these deficits may affect each individual with aphasia to a different degree. Similarly, in English relative clauses, using self-paced listening data from Caplan et al. (2015), Lissón et al. (2021a) also found that intermittent deficiencies, delayed lexical access, and slow syntax can explain the main processing deficits in IWA.

In our modeling, which follows the mapping in Lissón et al. (2021a) and Lissón et al. (2021b), intermittent deficiencies are implemented as increased stochastic noise in memory activations/availabilities. A higher noise value in IWA would mean more mistretrievals and presumably more parsing failures compared to unimpaired individuals. Delayed lexical access or slow syntax is assumed to delay the retrieval of the target item from memory, leading to a slowdown at the retrieval site in the activation-based model, and/or to misretrieval in both the activation-based and the direct-access model. In the DA model, which assumes backtracking as a key resource in parsing, resource reductions could disrupt this mechanism and lead to comprehension deficits.

In the current work, we focus on the role of the proposed processing deficits in the context of the activation-based and the direct-access models of cue-based retrieval. The interference effects that we model in the present paper could be also explained by other factors such as word order (non-canonical vs. canonical sentences), frequency, verbal short memory capacity (Tan & Martin, 2018) or incorrect representation of the verb argument

structure, among others. Alternative accounts will be presented in the general discussion. We use data from a picture-selection task and a visual-world experiment that tested the comprehension of pronouns and relative clauses in German (Pregla et al., 2022). We now introduce each linguistic construction in turn.

Experiment 1: Pronoun resolution

Consider sentence (3a). When the pronoun *er* (“he”) is encountered, cue-based retrieval predicts that a search for its antecedent is triggered, using the cues [+animate, +masculine, +singular]. The experiment makes use of the fact that for some verbs, the implicit subject of a sentential complement is coreferential with the main clause subject (subject control) while for others it is coreferential with the main clause object (object control; e.g., Chomsky, 1981; Comrie, 1985). The verb *versprechen* (“promise”) is lexically specified as a subject control verb (Müller, 2002). Therefore, in the context of cue-based retrieval, we assume that the cue [+subj] is set at the pronoun. The item whose features fully match these retrieval cues is the licensed antecedent, and therefore *Peter* is the target of the retrieval.

(3) a. **Mismatch.**

Peter<sub>+subj
+masc</sub> verspricht nun Lisa<sub>-subj
-masc</sub>, dass er<sub>{subj
masc}</sub> das kleine Lamm streichelt und krault.

Peter<sub>+subj
+masc</sub> promises now Lisa<sub>-subj
-masc</sub>, that he<sub>{subj
masc}</sub> the small lamb pets and ruffles.

‘Peter now promises Lisa that he will pet and ruffle the little lamb.’

b. **Match.**

Peter<sub>+subj
+masc</sub> verspricht nun Thomas<sub>-subj
+masc</sub>, dass er<sub>{subj
masc}</sub> das kleine Lamm streichelt und krault.

Peter<sub>+subj
+masc</sub> promises now Thomas<sub>-subj
+masc</sub>, that he<sub>{subj
masc}</sub> the small lamb pets and

ruffles.

‘Peter now promises Thomas that he will pet and ruffle the little lamb.’

Across the two sentences, the main clause object nouns, *Lisa* in (3a) and *Thomas* in (3b), partially match the retrieval cues from the pronoun. Both mismatch the [+subj] cue that the pronoun inherits from the verb, but *Thomas* matches the gender cue from the pronoun, which should lead to increased similarity-based interference. We will refer to sentences like (3a) as mismatch conditions, because the target noun (*Peter*) and the distractor noun (*Lisa*) do not share the same gender, and sentences like (3b), as match conditions.

A processing advantage in gender mismatch conditions in unimpaired populations has been observed in English by Badecker and Straub (2002) and Runner and Head (2014), but not by Chow, Lewis, and Phillips (2014). Laurinavichyute, Jäger, Akinina, Roß, and Dragoy (2017) reported mixed results for German. In the aphasia literature, Choy and Thompson (2010) and Engel, Shapiro, and Love (2018) found that IWA had difficulties in pronoun resolution, but these studies did not target the gender mismatch configurations that Pregla et al. (2022) tested, and that we model in the present work.

In Experiment 1, we model interference as a function of the gender cue at the pronoun. Based on cue-based retrieval theory, we predict a processing advantage in mismatch conditions relative to match conditions, and we aim to (a) compare how the activation-based and the modified direct-access model fit these data, and (b) evaluate the theoretical accounts of processing deficits in aphasia from their implementation in the models.

Experiment 2: Relative clauses

Relative clauses have been extensively studied in psycholinguistics. Subject relatives (SR) have been found to be easier to process than object relatives (OR) in multiple languages for both unimpaired controls (e.g., Fedorenko, Gibson, & Rohde, 2006; Gordon,

Hendrick, Johnson, & Lee, 2006; Grodner & Gibson, 2005; Staub, 2010; Staub, Dillon, & Clifton Jr, 2017) and for IWA (e.g., Burchert et al., 2003; Caplan et al., 2013, 2015; Caplan et al., 2007; Caramazza & Zurif, 1976; Dickey & Thompson, 2009; Pregla et al., 2021). The subject-object asymmetry in IWA and controls has been computationally modeled in the cue-based retrieval framework (Lissón et al., 2021a; Mätzig et al., 2018; Vasishth et al., 2019) using self-paced listening data and offline measures in English. The present study is the first to model number interference in relative clauses in German, in IWA and unimpaired controls.

Consider the sentences in (4). When the verb *badet/baden* (bathes/bathe) is encountered at the end of the sentence, two retrievals are triggered because the agent and the theme of the action expressed by the verb need to be identified. Our modeling focuses on the retrieval of the agent because that is the theoretically interesting event (this is explained below). Therefore, in (4), the arrow points towards the target of the retrieval, the agent. A + or a – preceding the number cue of the target and distractor indicates a match or a mismatch with the retrieval cue, which is shown at the retrieval site, the verb.

(4) a. **SR, match**

Hier ist [der Esel]_{+singular}, der [den Tiger]_{+singular} gerade badet_{singular}.

Here is the_{+singular} donkey who the_{+singular} tiger now bathes_{singular}.

‘Here is the donkey who bathes the tiger.’

b. **OR, match**

Hier ist [der Esel]_{+singular}, den [der Tiger]_{+singular} gerade badet_{singular}.

Here is the_{+singular} donkey who the_{+singular} tiger now bathes_{singular}.

‘Here is the donkey who the tiger bathes.’

c. **SR, mismatch**

Hier ist [der Esel]_{+singular}, der [die Tiger]_{+plural} gerade badet_{singular}.

Here is the_{+singular} donkey who the_{+plural} tigers now bathes_{singular}.

‘Here is the donkey who bathes the tigers.’

d. **OR, mismatch**

Hier ist [der Esel]_{+singular}, den [die Tiger]_{+plural} gerade baden_{plural}.

Here is the_{+singular} donkey who the_{+plural} tigers now bathe_{plural}.

‘Here is the donkey who the tigers bathe.’

In (4a) and (4b), both noun phrases in the sentence are singular (*der Esel*, *der/den Tiger*). Accordingly, both noun phrases have the retrieval cue [singular]; this is expected to cause similarity-based interference during the retrieval of the subject. By contrast, in (4c) and (4d), the second noun phrase is plural (*die Tiger*), which should result in easier identification of the subject, based on the retrieval cue from the verb ([singular] or [plural]). We will refer to sentences like (4c) and (4d) as mismatch conditions, because target and distractor do not share the same number, and sentences like (4a) and (4b), as match conditions. Both types of relative clauses should be easier to process in mismatch configurations compared to match conditions. Thus, (4c) and (4d) should be easier to process than (4a) and (4b), respectively.

In German, when the head noun is masculine (such as in our items), the morphological form of the relativizer (*der* for nominative, *den* for accusative) provides disambiguating information. Therefore, in our items, by the time the comprehender reaches the relativizer, they should be able to identify the agent or the theme of the relative clause due to the overt case marking. Retrieval should occur at the verb, and the number cue should facilitate processing in (4c) vs. (4a) and (4d) vs. (4b), because in (4c) and (4d) only the subject noun phrase matches the number cue at the verb.

Studies addressing the comprehension of subject vs. object relatives in German with case-unambiguous relativizers (such as our items) are scarce. Friederici, Steinhauer, Mecklinger, and Meyer (1998) tested the comprehension of these sentences in unimpaired

controls using ERP. They found a P600 in ORs relative to SRs at the relativizer. No significant difference in accuracies between the two conditions was reported. Studies investigating case-unambiguous subject vs. object relatives in IWA in German indicate that object relatives are generally more difficult to process for IWA. For example, Burchert et al. (2003) report that in case-unambiguous relatives the accuracies for OR are lower, relative to SR, in 4 out of the 7 IWA tested. Similarly, in a visual-world experiment, Adelt et al. (2017) also tested the comprehension of case-unambiguous relative clauses in IWA and control participants in German. In order to compare the accuracy estimates from the present paper with those of Adelt et al. (2017), we carried out a Bayesian logistic regression analysis of the accuracy data reported in Adelt et al. (2017). The analysis is available in the online supplementary materials. In the case-unambiguous relative clauses, IWA have lower accuracies than controls (-26% credible interval (CrI): [-42%, -13%]) and both groups have lower accuracies in object relatives (-13 % CrI: [-23%, -4%]). There is no indication of a group $\times$ RC type interaction (3 % CrI: [-5%, 11%]). Although the items in Adelt et al. (2017) and in Burchert et al. (2003) also included relative clauses with plural noun phrases, these relative clauses were case ambiguous. Therefore, these studies did not investigate whether a unique number cue facilitates processing. This is the empirical question that we address in this experiment.

The main goals in Experiment 2 are to compare the performance of the activation-based and the modified direct access model by modeling number interference in relative clauses, and to evaluate the different theories of processing deficits in aphasia from their implementation in the models.

Methods

The data that we model come from the experiments carried out by Pregla et al. (2022). The participants, procedure, and materials described here summarize the methods in Pregla et al. (2022). By contrast, the dependent variables and contrast coding described

here are specific to the present paper. Pregla et al. (2022) analyse the visual-world eye-tracking data, whereas we model the reaction times from the picture-selection task that followed the visual-world paradigm task.

Participants and procedure. Twenty-one IWA (9 females, mean age = 60.2 years, SD = 11.4; mean education = 15.2 years, SD = 3.2) and fifty control participants (32 females, mean age = 47.7 years, SD = 19.6; mean education = 18.1 years, SD = 4.0), all native speakers of German, took part in an auditory sentence-picture matching task combined with visual-world eye-tracking. Individuals with aphasia were in the chronic phase (at least one year after onset of the aphasia). More information about the patients is given in Appendix A. The procedure was as follows: At the beginning of the trial, a preview phase of 4000 ms was used to introduce two pictures to the participants. One of the pictures (target) corresponded to the correct meaning of the sentence, whereas the other picture (foil) depicted the opposite thematic interpretation. After the preview phase, an auditory recording of the sentence started playing. Sentences were presented at a normal speech rate, and participants were instructed to select the picture that matched the meaning of the sentence. The pictures were displayed until participants made a choice, or for a maximum time of 30 seconds. Once the participant pressed the choice button, the trial ended. During the trial, eye movements were recorded using a SensoMotoric Instruments eye-tracker (SMI RED250mobile; binocular tracking, Experiment Center version 3.7, sampling rate 250 Hz). The proportion of looks to the target picture against looks to the foil (or no picture) was calculated. The response time and the accuracy of the picture selection were also recorded. Each participant completed the experiments twice, in two sessions (test and retest), with a gap of approximately two months.⁵ Participants also performed a battery of tests in order to assess auditory and visual comprehension, morphological discrimination, and lexical decision latency.

⁵ The test vs. retest main effect is not included in our modeling (see the section on dependent variables) because the model structure had to be simplified due to convergence issues. The test-retest reliability for these data has been investigated in Pregla et al. (2021).

Materials. In Experiment 1, two conditions (match and mismatch, as in example 3), with 10 items each were included. Example pictures accompanying the pronoun sentences are shown in Figure (1). The pronoun items always used subject-control verbs, so that the target of the retrieval was always the first noun phrase.⁶ Control verbs were selected from the ZAS Database of Clause-Embedding Predicates (Stiebels et al., 2018).

Figure 1. Example pictures used in the picture-selection task in Experiment 1. For the sentences in example (3) the left picture is the target and the right picture is the foil.

In Experiment 2, 20 items per relative clause type (subject/object relative) were included. The noun phrase of the matrix clause (henceforth NP1) was always masculine and singular. Out of the 20 items, 10 had a singular embedded noun phrase (henceforth NP2), and 10 had a plural embedded noun phrase. The items were constructed using 10 bisyllabic transitive action verbs, and the noun phrases were always bisyllabic animal names. Example pictures for the relative clause conditions are given in Figure 2.

Dependent variables and contrast coding. To assess participants' lexical access speed, which is important for evaluating the delayed lexical access hypothesis of Love et al. (2008) and Ferrill et al. (2012), we computed their average reaction times in a lexical decision task, based on LEMO 2.0 (Stadie, Cholewa, & de Bleser, 2013). In this task, participants have to decide whether an auditorily-presented item is a word or a non-word. Participants responded by pressing one of the two buttons on a computer keyboard, and the accuracy and response times were recorded. We computed the average reaction times

⁶ The pronoun items that we use here were extracted from a larger experiment that also contained object-control verbs, and fillers.

Figure 2. Example pictures used in the picture-selection task in Experiment 2. These pictures correspond to the example sentences in (4).

in correct trials, which yielded a single measure (lexical decision time, LDT) for each participant that we use as a continuous predictor in the models. Response times in lexical decision tasks have been previously used as a measure of lexical access speed in IWA. For instance, Caplan et al. (2015) correlated the lexical decision times for correct responses with the accuracy and reading times in a self-paced listening task. We centered and scaled the LDT predictor within groups. An $\text{LDT} \times \text{group}$ interaction would thus tell us whether an increase in LDT leads to a larger increase in RT for IWA compared to controls.

Another predictor in the models is the proportion of fixations on the target picture (centered and scaled within groups) at the critical sentence region, where a retrieval is assumed to take place. We use the proportions of looks to the target at the critical region as a proxy for retrieval (see the next section for more details). The remaining predictors

used in both models were sum-coded, with the following contrasts: Group was coded with IWA as +1 and controls as -1; the high interference conditions (gender match in pronouns, number match in relative clauses) were coded as +1, and the low interference conditions (gender mismatch, number mismatch) as -1. In the relative clauses sub-experiment, the relative clauses were coded as OR +1, and SR -1.

We base our statistical inferences on the posterior distribution of the parameters, which we summarize with the mean and 95% credible interval (CrI). This is the convention used to report summaries of parameter values for which there is support in the data. When interpreting the estimates, the width of the CrI should be taken into account, as it shows the range of plausible parameter values that lie with 95% probability given our model and data.

For each experiment, two different versions of the activation-based model and the modified direct-access model were implemented.⁷ The models were implemented in Stan (Carpenter et al., 2017) and fitted in R (R Core Team, 2020) via the rstan package (Stan Development Team, 2020). The packages brms (Bürkner, 2017) and bayesplot (Gabry, Simpson, Vehtari, Betancourt, & Gelman, 2019) were used for examining and plotting the posterior distributions of the parameters. For each model, three chains each, with at least 6,000 iterations each were run. Each chain included at least 3,000 warm-up iterations. Convergence was assessed by checking that $\hat{R}$ was below 1.01 and by visually inspecting the convergence of the chains (Gelman et al., 2013). We also verified that the models could recover simulated parameter values. For both models, mildly informative priors were used (Nicenboim, Schad, & Vasishth, 2021; Schad, Betancourt, & Vasishth, 2021; Sorensen, Hohenstein, & Vasishth, 2016). Details about the implementation and the priors are available in Appendix C.

⁷ Initially, we intended to model the pooled data from both experiments. However, the complex structure of fixed and random effects lead to convergence issues in the modified direct-access model. Therefore, we ended up implementing two separate versions of each model, one for each experiment.

Modeling assumptions

Neither the activation-based model nor the direct-access model have a linking function that maps proportions of looks to a picture to retrieval times and/or retrieval probabilities of memory chunks. Therefore, we need to specify linking assumptions between fixations on the target picture, the assumed retrieval processes, and the reaction times and accuracies in the picture-selection task.

For the two sentence types, we assume two retrieval events. The first retrieval takes place in the middle of the sentence, at the *critical region*. In pronoun resolution, the critical region is the pronoun, and in relative clauses, it is the relativizer. Our linking assumption is that proportions of looks to the target at the critical region can be used as a proxy for retrieval. This assumption is based on the fact that the critical region provides the necessary cues to retrieve the target. Therefore, we predict that more looks to the target picture at the retrieval site correspond to a higher probability that the target has been retrieved at this point.

The second retrieval event happens at the verb region, that is, at the end of the sentence. In both experiments, the retrieval target must be re-accessed at this point, as it is the subject of the verb. We assume that the second retrieval is linked to the first, so that more looks to the target at the critical region (the pronoun/relativizer) go along with higher activation/availability, resulting in faster and/or more accurate retrieval at the verb region. As the picture-selection task takes place immediately after hearing the verb region, we assume that accuracies and RT in this task should show the interference effects predicted by the cue-based retrieval theory.

In what follows, we will present the implementation and the fits of the activation-based model and the modified direct-access model to the data in turn. We also present quantitative model comparisons, which allow us to assess the relative goodness of fit of each model to the data.

Activation-based model

The activation-based model can be implemented as a lognormal race of accumulators (Nicenboim & Vasishth, 2018): For the two experiments, we assume that there are two accumulators of noisy evidence that correspond to the retrieval candidates in memory, namely the first and the second noun phrase (NP1 or NP2, target or distractor). For each trial i , the finishing times FT for NP1 and NP2 are each sampled from a lognormal distribution with location μ_{NP1} or μ_{NP2} respectively, and scale σ . The accumulator with the faster FT_i determines both the selected picture (target or foil) and the reaction time for trial i . This implementation maps straightforwardly onto the notion of memory chunks with fluctuating activation values, with the chunk with the highest activation being retrieved on a particular trial.

The hierarchical structure of the models is implemented in the μ of both accumulators, which include fixed and random effects. The fixed effects added to μ_{NP1} and μ_{NP2} in the model for pronoun resolution are: Group (IWA vs. control), condition (match vs. mismatch), and the group $\times$ condition interaction. We also added the average reaction time from the lexical decision task (LDT), and the group $\times$ LDT interaction. Furthermore, we added the proportion of looks to the target at the critical region (fixations), the fixations $\times$ group interaction, and the three-way interaction fixations $\times$ condition $\times$ group. In addition, both μ included by-subject and by-item varying intercepts; the fixed effect of group included an adjustment by item, and the fixed effect of condition included an adjustment by subject. The parameter σ includes a fixed effect of group. In addition, the model for relative clause conditions also included a fixed effect for RC type, an RC type $\times$ group and an RC $\times$ condition interaction, and the RC $\times$ group $\times$ condition three-way interaction. The predictions of the activation-based model for the two experiments are as follows:

1. An increase in fixations to the target picture at the critical region should lead to a decrease in RT for the target accumulator in the picture-selection task, as we assume

that the first retrieval influences the second retrieval. If participants retrieved the target at the critical region, re-accessing it at the verb should be faster and more likely.

2. The mean finishing time of the target accumulator should be faster for the mismatch conditions relative to the match conditions. The mean of the distractor accumulator should be similar or slower in mismatch conditions relative to match conditions. That is, retrieval should be faster for mismatch than for match conditions, as interference slows retrieval.
3. IWA should have slower RT relative to controls, so IWA's μ should be higher. This would be in line with the *slow syntax* theory. Similarly, IWA should have a higher σ , that is, more noisy accrual of evidence, which would be in line with *intermittent deficiencies*.
4. If a delay in lexical access is causing processing difficulties in IWA, we would expect the effect of LDT to lead to a bigger increase in RTs for the target accumulator for IWA relative to controls, as higher RT for the target accumulator would indicate more difficulty in retrieving the target. This would be in line with *delayed lexical access*.

In addition, given earlier results (Adelt et al., 2017; Burchert et al., 2003), in Experiment 2, IWA should have longer mean finishing times for the target accumulator in OR compared to SR.

Modified direct-access model

We implement the modified direct-access model as a hierarchical mixture model in the Bayesian framework, following Lissón et al. (2021b). Mixture models integrate multiple generative processes in one model (see Nicenboim et al., 2021, chapter 20, for a tutorial on these models in Stan). The implementation of the modified direct-access model as a mixture model allows us to take into account the probability of backtracking as a latent

variable, and to fit RT-based measures. We assume that both correct and incorrect responses can be generated from one of two distributions: Responses without backtracking are generated from a given distribution with parameters μ and σ ; and responses with backtracking are generated from another distribution with parameters $\mu^* = \mu + \delta$ and σ , where δ is the time needed for backtracking. We begin this section by explaining the conceptual link between our parameters and the original direct-access model, which was originally evaluated using the speed-accuracy tradeoff paradigm (McElree, 2000, 2006).

The direct-access model assumes that the availability of items in memory determines their probability of retrieval. In our implementation, we map availability to the parameter θ , which is the probability of retrieval of the target. Memory availability has been found to decrease as a function of sentence complexity (A. E. Martin & McElree, 2011; McElree et al., 2003). Given that interference is expected to affect availability, we add a main effect of condition to θ . Because we expect IWA to have lower base availability compared to control participants, we also add a main effect of group. We also add a main effect of fixations, following the same logic as for the activation-based model: More fixations on the target at the critical region should lead to a higher probability of retrieval of the target at the verb. In order to evaluate the delayed lexical access theory, we include LDT as a fixed effect to θ , and the interaction $\text{LDT} \times \text{group}$. This interaction tests the *delayed lexical access theory* in IWA: If longer LDT leads to a larger decrease in θ for IWA, this would suggest that delayed lexical access lowers the probability of retrieval of the target, causing difficulties in the retrieval process.

The original direct-access model assumes that low availability can lead to a misretrieval or a failure in parsing. In a certain proportion of trials with a failed initial retrieval, a process of backtracking (or reanalysis) is triggered, which leads to correct retrieval of the target. This process requires some extra time (A. E. Martin & McElree, 2008; McElree et al., 2003). Our modified direct-access model assumes that backtracking can also fail. This is reflected in the added parameter θ_b , which represents the probability

of correct retrieval after backtracking. The additional parameter makes the modified direct-access model more suitable for modeling data from individuals with aphasia, as it allows for slow, incorrect responses. If IWA show a lower θ_b , relative to controls, this could point towards a disruption in the process of backtracking as a main source of comprehension difficulties in IWA. The parameter P_b stands for the probability of backtracking and estimates the proportion of trials for which backtracking is performed after an initial misretrieval. The parameter δ estimates the amount of time (in log ms) that backtracking takes. Main effects of group are added to the parameters θ_b , P_b and δ . P_b and θ_b additionally have by-subject random intercepts.⁸

The key difference between the activation-based model and the modified-direct access model is that the latter assumes retrieval times to be unaffected by interference. Interference can only indirectly affect response times through lower θ and the added cost of backtracking δ . Therefore, in the μ parameter, which estimates the mean average RT, we do not include an adjustment by condition, but we do include an adjustment by group, since retrieval may be slowed in IWA compared to controls. The noise parameter, σ , also has an adjustment by group, as IWA may have more variable retrieval times. The priors used, as well as the full hierarchical model, are shown in Appendix C.

The mixture process for a given trial i works as follows:

- (a) if the retrieval of the target succeeds, with probability θ , RT_i is drawn from $LogNormal(\mu, \sigma)$.
- (b) if the retrieval of the target fails ($1 - \theta$), backtracking is initiated with probability P_b . RT_i is sampled from $LogNormal(\mu + \delta, \sigma)$. After backtracking, the target is retrieved with probability θ_b , and the distractor with probability $1 - \theta_b$.
- (c) if the retrieval of the target fails and there is no backtracking, a misretrieval is predicted with probability $(1 - \theta) \cdot (1 - P_b)$, and RT_i is sampled from $LogNormal(\mu, \sigma)$.

⁸ Ideally, δ should also have a by-subject adjustment. However, this is a complex hierarchical model, and a by-subject intercept on δ led to convergence issues.

Notice that the probability of successful retrieval of the target, θ , and the probability of backtracking, P_b are assumed to be independent.

Correct and incorrect responses following backtracking (b), are expected to be slower, on average, than correct retrievals (a) and misretrievals without backtracking (c), due to the cost of backtracking δ . The RTs corresponding to an initial successful retrieval of the target (a) and to misretrievals without backtracking (c) are sampled from the same distribution. The predictions of the modified direct-access model for the two experiments are explained below.

1. Fixations to the target picture at the critical region should lead to an increase in the probability of retrieval of the target, as we assume that first retrieval influences the second retrieval. Therefore, the estimate of the main effect of fixations to the target on the probability of successful retrieval θ should be positive.
2. The probability of successful retrieval θ should be higher for non-interference conditions relative to interference conditions, that is, higher in mismatch vs. match conditions.
3. IWA should have slower RTs relative to controls, so IWA's μ should be higher. This would be in line with the *slow syntax* theory. Similarly, IWA should have a higher σ , which would be in line with *intermittent deficiencies*.
4. If IWA's slower access to items from memory leads to difficulties in the retrieval, we would expect LDT to lead to a bigger decrease in θ for IWA relative to controls. This would be in line with *delayed lexical access*.
5. We expect IWA to have a lower probability of backtracking, P_b , and a lower probability of retrieval of the target after backtracking, θ_b . This would be in line with the *resource reduction* theory, assuming that backtracking is a parsing resource that is impaired in IWA.

6. Similarly, we also expect IWA to have a higher cost of backtracking, δ , which would be in line with *slow syntax*.

In addition, given earlier results showing that OR are more difficult to process than SR (Adelt et al., 2017; Burchert et al., 2003), for the relative clause construction, θ should be lower in OR compared to SR.

We now move on to the modeling results, which will be presented separately for pronoun resolution and relative clauses.

Modeling results

Experiment 1

Activation-based model. In the pronoun resolution items, NP1 is always the target of the dependency. Therefore, μ_{NP1} accumulates evidence for the retrieval of the target, and μ_{NP2} for the retrieval of the distractor. Figure 3 shows the distribution of finishing times for the two accumulators (NP1 and NP2) across conditions and groups. The results confirm our predictions: IWA have longer finishing times relative to controls in both conditions. In controls, the means of the NP1 accumulator in the mismatch and match conditions are quite similar (1391 ms vs. 1465 ms), although responses are faster on average in the mismatch condition, as expected. IWA show a larger effect of interference: The mean of the NP1 accumulator in the mismatch condition is 4532 ms, compared to 5735 ms in the match condition. The interference effect can also be seen in the overlap of the distributions within each plot. Whereas the distributions lie far apart from each other in controls, in IWA, the distributions overlap. This indicates that IWA are more likely to retrieve the distractor than controls, especially in the interference condition (match). In general, the plots show that IWA experience a bigger interference effect. This is in line with the estimates for the group $\times$ condition interaction (μ_{NP1} : 199 ms, CrI: [81, 322] ms and μ_{NP2} : 1424 ms, CrI: [400, 2720] ms).

Figure 3. Distribution of the accumulators of evidence across groups and conditions for the Experiment 1 (pronoun resolution). The dashed lines represent the means of the distributions.

With regard to the fixed effects on μ_{NP1} and μ_{NP2} , due to space limitations, we will only comment on the estimates that are relevant to the processing theories of aphasia that we are evaluating. The estimates for all parameters in this model and their credible intervals are shown in Appendix D.

The NP1 accumulator showed an indication of an $LDT \times \text{group}$ interaction (836 ms, CrI: [539, 1152] ms), but no indication of such an interaction was observed for the NP2 accumulator. This suggests that additional time needed for lexical access leads to a larger slowdown in IWA in the target accumulator, as predicted by the delayed lexical access theory. The estimates for fixations and the fixations $\times$ group interaction do not point in the predicted direction: An increase in fixations on the target picture leads to an increase in RTs in both accumulators (NP1: 41 ms, CrI: [-77, 160] ms; NP2: 518 ms, CrI: [-141, 1212] ms). However, due to large uncertainty around the estimates, the results are also

compatible with no effect of fixations.

Finally, as predicted under the intermittent deficiencies theory, IWA have higher noise than controls (σ_{IWA} : 0.65 log ms, CrI: [0.62,0.69] log ms, $\sigma_{controls}$: 0.28 log ms, CrI: [0.27,0.29] log ms).

Modified direct-access model. We begin by assessing the posterior distribution of θ , which is the probability of retrieving the target during the first retrieval attempt. Figure 4 shows that the probability of retrieval of the target is very high for controls: The mean of the distribution lies above 95% in both conditions (CrI mismatch: [96, 98]%, CrI match: [98, 99]%). By contrast, IWA show lower retrieval probabilities overall. This can be also seen in Figure 4, where IWA's mean estimate for match is 55% CrI: [47, 62]%, whereas the estimate for mismatch is 72% CrI: [66, 77]%. The group $\times$ condition interaction is inconclusive (2 CrI: [-1, 5]%).

Figure 4. Posterior distribution of the probability of initial retrieval of the target, θ for the two groups, in the pronoun conditions. The vertical lines stand for the means of the distributions, and the shaded areas indicate the 95% credible interval.

A unit increase in LDT leads to -5% CrI: [-8, -1]% in θ , and a negative LDT $\times$ group interaction (-9% CrI: [-12, -7]%) is consistent with the assumption that IWA are more affected by increased LDT. There was neither an indication of an effect of fixations (2% [-1, 5]%), nor of a fixation $\times$ group interaction (-2% CrI: [-5, 2]%). This means that for both groups, there is no indication that an increase in fixations to the target picture led to an increase in the probability of successful retrieval of the target.

Figure 5. Posterior distribution of the probability of retrieval of the target after backtracking, for the two groups, in the pronoun conditions. The dashed lines stand for the means of the distributions.

The estimated probability of backtracking for IWA is 22% CrI: [13, 31]% compared to 66% CrI: [51, 79]% for controls. The distribution of the cost of backtracking, δ , is centered around 5592 ms, CrI: [3924, 7738] ms for IWA, and around 2827 ms, CrI: [2277, 3551] ms for controls. The probability of retrieval of the target after backtracking, θ_b , is shown in Figure 5. Backtracking leads to the retrieval of the target around 84% of the time for controls (CrI: [70, 94]%), and 58% of the time for IWA (CrI: [42, 73%]). Slower and less successful backtracking is consistent with slow syntax and resource reduction in IWA.

Finally, IWA's μ (2376 ms, CrI: [2079, 2701] ms) is higher than controls' μ (1320 ms, CrI: [1202, 1447] ms); and IWA also have a larger estimate of noise (0.46 log ms, CrI:

[0.43,0.5] log ms) relative to controls (0.24 log ms, CrI: [0.23,0.25] log ms), as predicted under the slow syntax and intermittent deficiencies theories.

Experiment 2

Activation-based model. In the relative-clause items, μ_{NP1} stands for the retrieval of NP1 as the agent of the action, whereas μ_{NP2} stands for the retrieval of NP2 as the agent. Depending on the trial, NP1 (in subject relatives) or NP2 (in object relatives) will be the target of the retrieval, as we model the retrieval of the agent.

Figure 6 shows the distribution of finishing times of the two accumulators in subject relative clauses. As expected, IWA have higher finishing times than controls across conditions. The mean of the NP1 accumulator (target) is roughly the same across conditions, whereas the mean of the NP2 accumulator (distractor) is higher in the condition than in the match condition. In general, controls show almost no overlap between the distributions, which indicates that controls retrieve the target (NP1) most of the time. By contrast, in IWA, the two distributions partially overlap. This suggests that in subject relatives, IWA retrieve the target more often than the distractor; yet IWA retrieve the distractor more often than controls.

Figure 7 shows the distribution of finishing times of the two accumulators in object relative clauses. IWA have higher finishing times than controls across conditions, and both groups have slightly lower finishing times in the NP2 accumulator (target) in mismatch vs. match conditions. Crucially, in the match condition, for IWA (right upper panel in Figure 7, light dashed line) the mean of the NP1 accumulator is lower than the mean of the NP2 accumulator. Since NP2 is the retrieval target in object relatives, the pattern indicates that in the match condition, IWA retrieve the distractor more often than the target. That is, in the match condition, IWA are more likely to misinterpret the sentence than to interpret it correctly. However, in the mismatch condition, the mean of the two accumulators overlap, which indicates that IWA are equally likely to retrieve NP1 or NP2 on average.

Figure 6. Distribution of the accumulators of evidence across groups and conditions for subject relative clauses. The dashed lines indicate the means of the distributions.

Comparisons between Figure 6 and Figure 7 show that controls perform similarly in subject and object relatives, whereas IWA display a subject-object asymmetry: IWA are estimated to correctly interpret subject relatives most of the time. By contrast, IWA are estimated to misinterpret object relatives more often, especially in the match condition.

The model estimates for the fixed effects and interactions on μ_{NP1} and μ_{NP2} are shown in Appendix D. No indication of an effect was found for condition or the condition $\times$ group interaction, but there was a RC type $\times$ condition interaction on μ_{NP2} (631 ms, CrI: [385, 884] ms): Interference (match) in OR lead to higher finishing times for μ_{NP2} relative to no-interference (mismatch). The three-way interaction RC type $\times$ group $\times$ condition for μ_{NP2} (-249 ms, CrI: [-491, -10] ms) indicates that the effect of condition within RC is different for the two groups in the μ_{NP2} accumulator: In the SR trials, the difference between match and mismatch conditions is bigger for controls. By contrast, in OR trials, the difference between match and mismatch conditions is bigger for IWA.

Figure 7. Distribution of the accumulators of evidence across groups and conditions for object relative clauses. The dashed lines indicate the means of the distributions. Note that in the mismatch condition, for IWA, the means of the two distributions overlap.

There was no indication of an $LDT \times \text{group}$ interaction, a $LDT \times \text{condition}$ interaction, or a $LDT \times \text{condition} \times \text{group}$ interaction. There was an effect of fixations on μ_{NP2} (289 ms, CrI: [61, 521] ms). This main effect is uninformative, given that NP2 was the retrieval target in OR but not in SR. There was no indication of a fixations $\times$ condition interaction or a fixations $\times$ group $\times$ condition interaction, so that the role of fixations remains inconclusive. Finally, as predicted, IWA have higher noise than controls (σ_{IWA} 0.55 log ms, CrI: [0.53, 0.57 log ms], $\sigma_{controls}$ 0.31 log ms, CrI: [0.3, 0.32 log ms]).

Modified direct-access model. The posterior distributions of θ , the probability of initial retrieval of the target, by group and condition are displayed in Figure 8. While controls have a slightly lower θ in OR relative to SR in the match conditions, both SR and OR have a similar θ in mismatch conditions, around 95%. This indicates that the number mismatch facilitates the retrieval of the target, especially in OR. The number mismatch

also benefits IWA on average, but IWA exhibit a stronger subject-object asymmetry, irrespective of the number manipulation, with higher θ in SR relative to OR for both match and mismatch conditions.

Figure 8. Posterior distribution of the probability of retrieval of the target (θ) across groups and conditions in relative clauses. The vertical lines stand for the means of the distributions, and the shaded areas represent the 95% credible interval.

The estimates of the model confirm what Figure 8 shows. The effect of condition (-10% CrI: [-13, -6]%) suggests that match conditions elicit a lower θ across the board, but a condition $\times$ group interaction (7% CrI: [3, 10]%) suggests that the effect of condition is stronger for controls than for IWA. There was no indication of a RC type $\times$ condition interaction (-1% CrI: [-5, 2]%), nor of a RC type $\times$ condition $\times$ group interaction (1% CrI: [-3, 4]%). The effect of RC type (-13%, CrI: [-18, -9]%) and the RC type $\times$ group

interaction (-7%, CrI: [-12, -3]%) indicate that object relatives are more difficult to process than subject relatives, and more so for IWA than for controls.

There was no indication of an effect of LDT on θ (-3%, CrI: [-8, 2]%), nor of a group $\times$ LDT interaction (3%, CrI: [-2, 8]%). A unit increase in fixations led to -2%, CrI: [-5, 1]% on θ , and the interaction group $\times$ fixations 4%, CrI: [1, 7]% suggests that the effect of fixations is different for IWA and control participants: In IWA, an increase in fixations of looks to the target leads to a higher θ .

The estimated probability of backtracking given an initial incorrect retrieval is 35% CrI: [20, 50]% for IWA, whereas for controls it is 87% CrI: [83, 91]%. The posterior distribution of θ_b is shown in Figure 9: After backtracking, IWA retrieve the target about half of the time. By contrast, controls retrieve the target more than 80% of the time. In addition, IWA are estimated to need 3457 ms, CrI: [2425, 4659] ms for backtracking, whereas controls need 1829 ms, CrI: [1637, 2032] ms.

Posterior distribution of θ_b

Figure 9. Posterior distribution of the probability of retrieval of the target after backtracking (θ_b) across groups in the relative clauses experiment.

Finally, as predicted, μ is higher for IWA (3744 ms, CrI: [3304, 4234] ms) than for controls (1613 ms, CrI: [1492, 1736] ms), and σ is also higher for IWA (0.41 log ms, CrI: [0.38 log ms, 0.44 log ms]) than for controls (0.24 log ms, CrI: [0.23 log ms, 0.24 log ms]).

Discussion

In the two models, the location and scale parameters of the log-normal distribution from which RT are sampled (μ and σ) were consistently higher for IWA than for controls. We linked these parameters to the slow syntax and intermittent deficiencies theories, respectively. Both models thus seem to be generally in line with these two theories of processing deficits in aphasia. We will now discuss the implications for the remaining theories within each model.

Activation-based model

We hypothesized that the accumulators in the activation-based model should reflect the interference effect predicted by cue-based retrieval theory; namely, lower mean finishing times for the target accumulator, and similar or higher mean finishing time for the distractor accumulator in the mismatch conditions compared to the match conditions. The accumulators show this pattern across the two experiments. In addition, in Experiment 2, the distribution of the accumulators across relative clause types show that IWA experience a subject-object asymmetry, i.e., IWA have more difficulties processing object relatives.

The conclusions for the rest of our predictions are more complex, since the results differ across the two experiments. For instance, a group $\times$ LDT interaction was found for the target accumulator in pronoun resolution. This interaction indicates that slower lexical access leads to increased processing difficulty for IWA, as predicted by the delayed lexical access theory. However, there was no indication of such an interaction in relative clauses. We therefore conclude that more research is needed in order to establish the role of delayed lexical access in the activation-based model. Speculatively, it could be that a retrieval triggered by a pronoun is more strongly affected by delayed lexical access than one triggered by a verb: Our pronouns were directly coreferential with a previous noun phrase (*Peter ... er*), while the association between a verb and its arguments is more indirect.

The effect of looks to the target at the critical region also remains inconclusive. No

effect of fixations was found in pronoun resolution. In relative clauses, an effect of fixations was found for the NP2 accumulator, but no indication of an interaction between fixations and RC type was found. Given that NP2 was the retrieval target in OR but not in SR, the main effect of fixations is uninformative.

Modified direct-access model

We expected a lower probability θ of retrieval for the target in the match versus mismatch conditions. The data from both experiments are in line with this prediction. In addition, in Experiment 2, IWA show a large effect of relative clause type, irrespective of the condition: IWA have more difficulties understanding object relatives compared to subject relatives. This subject-object asymmetry is broadly in line with the accuracies in Adelt et al. (2017), although Adelt et al. (2017) found this pattern in both IWA and controls.

According to the delayed lexical access theory, IWA should be more affected by delays in lexical access, as measured by a lexical decision task. The observed group $\times$ LDT interaction lends some support to this theory in the pronoun resolution sub-experiment, but not in relative clauses. Therefore, the effect of delayed lexical access in the modified direct-access model remains inconclusive. The effect of fixations is also inconclusive: Although in relative clauses there is some indication that fixations at the critical region may lead to a increase in the probability of retrieving the target for IWA, no effect of fixations was found in pronoun resolution.

Finally, the probability of backtracking is consistently lower for IWA than for controls, as is the probability of retrieval of the target after backtracking (θ_b). This pattern is expected under the resource reduction theory. In addition, the average cost of backtracking, δ , is twice as high for IWA compared to controls in both experiments. This adds support for the slow syntax theory.

Model comparisons

The activation-based model and the modified direct-access model make different assumptions about the retrieval mechanism, and thus the generative process behind the observed data. Within the framework of each model’s assumptions, conclusions can be drawn about plausible underlying deficits. However, one crucial question remains open: Which model fits the data better overall? In order to answer this question, we performed 10-fold cross-validation (Vehtari, Gelman, and Gabry, 2017; see also Nicenboim et al. (2021), chapter 17, for a tutorial on carrying-out cross-validation for Bayesian models such as the ones discussed here). This is a standard procedure in machine learning for quantifying the relative goodness of fit of two or more models. Importantly, cross-validation can also be applied when the models assume different generative processes, as is the case with the activation-based and the modified direct-access models.

The procedure for 10-fold cross-validation is as follows: The data are partitioned into 10 balanced subsets containing about the same amount of data per subject.⁹ One of the 10 subsets is held out, and the model is fit to the remaining subsets. The posterior distributions from the resulting model are used to compute predictive accuracy on the held-out subset. This is repeated 10 times, so that all subsets are covered. The expected log pointwise predictive density, $\widehat{elpd}$, is then calculated as a measure of predictive accuracy. $\widehat{elpd}$ is the summed log-likelihood of all observed, held-out data points under each model. Models are compared by computing the difference in $\widehat{elpd}$, $(\Delta\widehat{elpd})$, with higher $\widehat{elpd}$ indicating better predictive fit. Because $\widehat{elpd}$ is an estimate, the difference in $\widehat{elpd}$ between two models has an associated standard error, which has the standard frequentist interpretation: $\Delta\widehat{elpd} \pm 2 \times SE$ gives a 95% confidence interval. If the difference in $\widehat{elpd}$ between the models is greater than $2 \times SE$, we conclude that there are grounds to assume

⁹ Given that our dataset contains data from two experimental sessions (test and retest), an alternative way to perform cross-validation would be to train the models on the test data and to use the retest data to compute predictive accuracy. However, we chose to use the pooled data from each of the two experiments, in order to maximize the amount of data, especially for IWA.

that the model with the higher $\widehat{elpd}$ provides the better fit for the given data.

The results of the cross-validation are shown in Table 1. In pronoun resolution, the modified direct-access model has a predictive advantage, but since the SE of $\widehat{\Delta elpd}$ is large, the result is not conclusive. In relative clauses, the activation-based model has a clear advantage over the modified direct-access model. In order to find out which group and/or condition is driving the advantage, we can compute $\widehat{\Delta elpd}$ separately for each group and each condition. The results are shown in Figure 10. It appears that the advantage of the activation-based model over the modified direct-access model mostly comes from fitting the data of control participants, especially in the OR, mismatch conditions ($\widehat{\Delta elpd}$ 163, SE 66).

Table 1

Differences in $\widehat{elpd}$ between the two models and their corresponding SE. Positive differences indicate an advantage for the activation-based model, whereas negative differences indicate an advantage for the modified direct-access model.

Model	$\widehat{\delta elpd}$	SE
Pronoun resolution	-109	133
Relative clauses	403	167

We also evaluated the predictive performance of the original direct-access model, i.e., a model in which backtracking can only lead to the retrieval of the target. The $\widehat{\Delta elpd}$ between the original direct-access model and the modified direct-access model is -41, SE 134 for pronoun resolution; and -175, SE 166 for relative clauses. The negative $\widehat{\Delta elpd}$ estimates indicate that the modified direct-access model may have a better predictive performance, but given the large SE, the $\widehat{\Delta elpd}$ are inconclusive. When comparing the activation-based model with the original direct-access model, the difference is not conclusive in the pronoun experiment ($\widehat{\Delta elpd}$ -68, SE 140), but in relative clauses, the activation-based model performs better ($\widehat{\Delta elpd}$ 578, SE 173). Thus, in relative clauses, the activation-based model outperforms both the original and the modified-direct access model.

Figure 10. Graphical representation of the $\widehat{\Delta elpd}$ between the activation-based and the modified direct-access model across groups and conditions. The dot stands for the $\widehat{\Delta elpd}$ and the bars indicate to the 95% confidence interval. Positive values indicate an advantage for the activation-based model, and negative values indicate an advantage for the modified direct-access model (MDA).

General discussion

This is the first-ever computational investigation of competing models of similarity-based interference in German language comprehension in IWA and unimpaired controls. We investigated interference in two linguistic constructions, namely pronoun resolution and relative clauses. Two models of cue-based retrieval were implemented in a Bayesian framework: The activation-based model of Lewis and Vasishth (2005) and a modified version of the direct-access model of McElree (2000, as implemented in Nicenboim and Vasishth, 2018). The activation-based model assumes a direct connection between retrieval latency and retrieval probability for memory items, whereas the modified direct-access model assumes a constant retrieval latency, along with a costly backtracking

mechanism if retrieval fails. In the original direct-access model, backtracking leads to the correct retrieval of the target item from memory (McElree, 1993). In our modified direct-access model, backtracking can fail, leading to a costly misretrieval. We argue that this is a more suitable model for individuals with aphasia, as it can account for slow incorrect responses, a pattern that is frequently found in the aphasia literature (Adelt et al., 2017; Hanne et al., 2015; Lissón et al., 2021b; Pregla et al., 2021). The predictive performance of the two models was compared against data from a visual-world experiment (Pregla et al., 2021), using the reaction time and accuracy in the picture selection task as dependent variables. Looks to the target at the critical sentence region, where retrieval is assumed to occur, were used as a predictor, along with the mean reaction times from a lexical decision task. We linked the parameters of each computational model to prominent theories of processing deficits in aphasia, aiming to answer two main questions: (a) Which model is better able to fit the data from IWA and control participants across the two experiments? and (b) What do the parameters in each model tell about the processing deficits and about interference in IWA? We will now discuss the answers to these questions, as well as the relation of our results to prior work in computational modeling of processing deficits in aphasia.

First, both models of retrieval perform well across the two linguistic constructions tested. The activation-based model outperforms the modified direct-access model in the relative clauses experiment, mainly because it provides a better predictive fit for the data from control participants. However, both models perform similarly at fitting data from IWA. In pronoun resolution, the two models show similar predictive fit across groups and across conditions.

Second, with regards to the underlying processing deficits in aphasia, both models are in line with slow syntax (Burkhardt et al., 2008; Burkhardt et al., 2003) and intermittent deficiencies (Caplan et al., 2013). Resource reduction (Caplan, 2012; Caplan et al., 2007), as implemented here, can only be evaluated with respect to the modified direct-access

model, and the results show that the model is in line with this deficit. There was no strong indication in our data, across the two experiments and for both both models, that delayed lexical access (Ferrill et al., 2012; Love et al., 2008) is a source of processing deficits in IWA: The predicted relationship between individual lexical decision latency and participant group was only found in some conditions. More experiments are needed in order to explore the role of this deficit.

Regarding the effect of similarity-based interference, based on the results for the activation-based model, we can conclude that in pronoun resolution, IWA are more sensitive to gender interference than control participants. The interaction group $\times$ condition was inconclusive in the modified-direct access model. Both models estimate that in relative clauses, the effect of number interference is rather small for both groups. The models suggest that IWA experience a subject-object asymmetry, whereas control participants do not. Below, we discuss some possible explanations of the subject-object asymmetry in IWA and the comparatively small effect of number mismatch in relative clauses.

Subject-object asymmetry

The subject-object asymmetry in relative clauses in IWA is in line with the canonicity effects reported in several German studies with IWA (e.g., Adelt et al., 2017; Burchert & de Bleser, 2004; Burchert et al., 2003; Hanne et al., 2011; Pregla et al., 2021). Canonicity effects refer to the fact that sentences with a non-canonical order (e.g., object-subject-verb in German) are more difficult to process than sentences with a canonical order. Canonicity effects could be orthogonal to the memory retrieval process, and could be caused by frequency, as canonical sentences are more frequent than non-canonical ones. However, neither the activation-based model nor the (modified) direct-access model currently take into account frequency effects in sentence structures. An interesting test for both models would be to implement frequency structure effects and to

test the models' predictions against data from IWA.

Figure 11. Descriptive statistics for the relative clauses experiment. The dots stand for the means, and the error bars show the standard error of the means.

In contrast to English, where subject and object relative clauses are distinguished by word order, successful comprehension of German case-unambiguous relative clauses requires comprehenders to use grammatical case as a cue to correctly identify the agent and the theme of the verb; both in subject and in object relatives. Given that controls' performance was at ceiling in both relative clause types (see Figure 11), we conclude that controls were able to use case-marking cues accurately. This is consistent with previous studies on relative clause processing in German (e.g., Friederici et al., 1998). Our data also shows that IWA have difficulties understanding relative clauses, especially object relatives. However, cue-based retrieval cannot explain this subject-object asymmetry: Both in subject and in object relative clauses, the verb is clause-final and two NPs have to be retrieved, one that is adjacent to the verb and one that is not. Consequently, cue-based retrieval would predict no processing difference between subject and object relatives in German. It is thus not clear why processing object relatives in German should be more difficult from a purely retrieval-based point of view.

One way to explain the subject-object asymmetry would be to assume that IWA have

difficulties using case features in relative clauses. A possible explanation is that IWA may be more sensitive to case attraction. Case attraction is analogous to the well-studied phenomenon of number attraction, which has been explained in terms of feature percolation (e.g., Eberhard, 1997; Nicol, Forster, & Veres, 1997). In relative clauses, case attraction posits that processing is facilitated when the relativizer and its antecedent have the same case (Bader & Meng, 1999). If the head noun and the relativizer mismatch in case, the case feature of the head noun could percolate down to the relativizer, overriding its original case, and creating a misinterpretation. Once the verb is reached, at the end of the sentence, and the subject needs to be retrieved, the misinterpretation in the case feature of the relativizer could lead to a costly reanalysis process. Bader and Meng (1999) and Bader, Meng, and Bayer (2000) claim that case attraction occurs with dative-marked pronouns. In their account, the feature [+dative] percolates upwards to the head noun. Czypionka, Dörre, and Bayer (2018) refer to this configuration as inverse case attraction. Other studies testing unimpaired populations in German have shown that case attraction can also happen with nominative/accusative cases, and that feature percolation can also happen downwards, from the head noun to the relativizer (Logačev and Vasishth, 2012, experiment 2; Schlesewsky, 1996, reported as experiment 1 in Fanselow, Schlesewsky, Cavar, and Kliegl, 1999). However, these studies tested complex center-embedded relative clauses that are very different from our items.

In our data, assuming that IWA have a larger effect of case attraction could explain the subject-object asymmetry. Consider again sentence (4b), repeated here as (5). In relative clauses with masculine head nouns, such as in our items, the case attraction theory would predict that subject relatives are easier to process because both the head noun and the relativizer have the [+nominative] feature.

- $$\begin{array}{c} +\text{nom} \\ \hline \downarrow \end{array}$$
- (5) Hier ist [der Esel]_{+sing}^{+nom}, den_{+sing}^{+acc} [der Tiger]_{+sing}^{+nom} gerade badet_{+sing}^{+nom}.

Here is the_{NOM} donkey who_{ACC} the_{NOM} tiger now bathes.

‘Here is the donkey who the tiger bathes.’

The first noun phrase, *der Esel*, has the features [+nominative, +singular]. The relativizer, *den*, has the features [+accusative, +singular]. However, due to case attraction, the relativizer could end up encoded in memory with features [+nominative, +singular]. The second noun phrase, *der Tiger*, also has features [+nominative, +singular]. At the verb *badet* (bathes), when the retrieval of the subject is triggered with cues [nominative, singular], both noun phrases would share the retrieval cues [+nominative, +singular]. In both the activation-based and the modified direct-access model, this configuration would lead to misretrievals of the distractor. In the modified direct-access model, after this initial misretrieval, in a certain proportion of the trials, IWA could initiate a backtracking process, which would fail more than half of the time (as estimated by θ_b). Therefore, in combination with a cue-based retrieval mechanism, in IWA, case attraction would predict more misretrievals and slower processing times in object relatives compared to subject relatives. Control participants may experience case attraction less often than IWA, and if an initial misretrieval occurs, they can backtrack and correctly retrieve the target with a very high probability. Thus, case attraction could also explain the pattern in the data of control participants, which show slightly lower accuracies and slightly higher RT in object compared to subject relatives, as shown in Figure 11. The role of feature percolation in the activation-based model has been recently investigated by Yadav, Smith, and Vasishth (2021). Their results support the view that in unimpaired populations, feature percolation feeds retrieval processes, suggesting that a hybrid model may explain similarity-based interference better. It remains to be seen whether such a hybrid model would provide a better fit for data from individuals with aphasia.

Alternatively, the subject-object asymmetry could also be explained by the noisy channel or rational inference account of sentence comprehension (Gibson, Bergen, & Piantadosi, 2013). This account claims that sentence comprehension involves a Bayesian computation of the probabilities of possible intended sentences given a perceived sentence

that may have undergone distortions, for instance because of noise in the processing system. The impairments in IWA are assumed to increase the likelihood of sentence distortions due to an increased amount of noise (Gibson, Sandberg, Fedorenko, Bergen, & Kiran, 2016; Warren, Dickey, & Liburd, 2017), which could lead IWA to rely more on their prior probability of a sentence interpretation. Prior sentence expectations are based on construction frequency and world knowledge. Essentially, because the incoming perceptual data are noisy, IWA are predicted to use the prior to infer that the speaker probably intended the more frequent subject-relative structure.

Number mismatch

The results of the models show that for IWA, the presence of two candidate NPs with distinctive number features is of limited use in both subject and object relatives with regard to successful comprehension (see also the descriptive statistics for relative clauses, split by condition, in Appendix B). The modified direct-access model estimates no effect of number mismatch for IWA. Although the activation-based model estimates that number mismatch between the NPs slightly increases the probability of retrieving the target in object relatives, the target is only retrieved about half the time in these conditions. It thus seems that for IWA, the effect of RC type is greater than the effect of number interference.

One possible explanation for the differential effects of number marking and RC type is that IWA may not weight case and number cues equally. The cue-weighting proposal, implemented by Engelmann (2016) in the framework of the Lewis and Vasishth (2005) model, claims that depending on the linguistic structure, some retrieval cues may be weighted higher than others (see also Engelmann et al., 2019; Vasishth et al., 2019). This assumption is motivated by research in individual differences in the memory literature, which has shows that some individuals learn to use certain retrieval cues more efficiently than others (e.g., Danker, Fincham, & Anderson, 2011). In sentence processing, it has been argued that structural and non-structural cues could be weighted differently (e.g., Cunnings

& Sturt, 2014; Dillon et al., 2013; Parker & Phillips, 2017). Differences in cue weighting could be integrated in both the activation-based and the direct-access model, as both models rely on retrieval cues. Speculatively, it could be that IWA weight case and number cues differently, and that the retrieval in relative clauses is mostly guided by case cues.

Studies that have investigated processing of number and case in IWA in German provide mixed evidence with regard to this proposal. For instance, Hanne et al. (2015) investigated IWA’s use of case and number cues to interpret semantically reversible SVO vs. OVS sentences in German. Their data indicate that processing of case marking may be more impaired than processing of number marking. This contrasts with the results in Adelt, Burchert, Adani, and Stadie (2020), who tested case-unambiguous vs. case-ambiguous, number-disambiguated object relatives. The authors found that IWA have a general processing advantage in the case-unambiguous conditions. The study of Adelt et al. (2020) supports the idea that IWA may rely more on case cues than on number cues in relative clauses. However, neither Adelt et al. (2020), nor Hanne et al. (2015) included both case and number cues within the same items. Our modeling shows that when both case and number cues are included in a sentence, IWA do not benefit from the extra number cue.

Recently, a Bayesian version of the Lewis and Vasishth (2005) model has been developed that includes an estimation of cue-weighting at the individual level (Yadav, Paape, Smith, Dillon, & Vasishth, 2021). An interesting future direction would be to investigate whether differences in cue-weighting between individual IWA and control participants could account for our relative clause data. Similarly, it would be interesting to develop a hybrid model that accounts for both case attraction and cue weighting, along the lines of the work by Yadav, Smith, and Vasishth (2021).

Comparison with previous work

Lissón et al. (2021a) investigated English relative clause processing in IWA vs. controls using a large-scale dataset from Caplan et al. (2015). Lissón et al. found an

agent-first bias for control participants in English: In non-canonical clauses, such as object relatives, unimpaired controls tend to initially assign the agent role to the first noun phrase in the sentence, which is incorrect in object relatives. By contrast, IWA do not show an agent-first bias. The agent-first bias in unimpaired controls has been attested in visual-world studies in both English (Mack, Wei, Gutierrez, & Thompson, 2016, passives) and German (Hanne et al., 2015, OVS sentences; Hanne et al., 2015, object relatives). In these studies, control participants initially show increased looks to the foil picture in non-canonical sentences. The foil picture in non-canonical sentences depicts the canonical interpretation of the sentence. As soon as they hear the relevant morphological cues (e.g., the relativizer in unambiguous German relative clauses), they start looking at the target picture. In the study by Lissón et al. (2021a), which modeled self-paced listening data, this processing bias was reflected in the estimates for the direct-access model. Controls had a lower probability of initial correct retrieval than IWA in object relatives (controls 40%, IWA 50%). That is, controls were estimated to initially retrieve the distractor more often than the target in object relatives. The model could still account for the higher accuracy of controls by assuming a high probability of backtracking for controls (80%) relative to IWA (20%). This pattern supported the notion that controls initially processed the first noun phrase in object relatives as the agent, until they revised and corrected their interpretation by backtracking. Surprisingly, in the present modeling of the German data, we do not see such an agent-first bias. In the present study, controls did not have a lower θ relative to IWA, and controls' θ was always above 90% for all conditions. One possibility is that in our modeling, the RT at the end of the sentence do not reflect the agent-first bias, given that the initial interpretation has already been revised at this point.

With respect to model comparisons, Lissón et al. (2021a) found that the activation-based model had a predictive advantage over the original direct-access model, although the difference was not decisive, given the large SE of the $\widehat{\delta elpd}$. In the present study, we show that in relative clauses in German, the activation-based model furnishes a

better fit than both the original and the modified direct-access model. Our results contrast with Nicenboim and Vasishth (2018), who compared the predictive performance of the activation-based model and the original direct-access model using self-paced reading data from unimpaired controls in German (Nicenboim et al., 2018). Nicenboim and Vasishth (2018) found that the original direct-access model provided a better fit to their data. However, the data modeled in Nicenboim et al. (2018) differ from our data in one important aspect: In correct trials (i.e., trials with correct responses to the comprehension question), RTs were on average higher than the RTs in incorrect trials. This pattern in Nicenboim’s data is crucial, because higher RTs for correct responses is what the original direct-access model assumes. Consequently, the advantage in predictive performance of the original direct-access model vs. the activation-based model came from the slow, correct responses. By contrast, our data shows the opposite pattern. Correct responses are, on average, faster than incorrect responses, especially for IWA. Although in the present paper we have implemented a modified direct-access model that can account for slow incorrect responses, the cross-validation shows that the activation-based model outperforms both the original and the modified-direct access model in relative clauses in German.

Overall, our results are in line with previous modeling work in sentence comprehension in aphasia using the activation-based model (Lissón et al., 2021a; Mätzig et al., 2018; Patil, Hanne, et al., 2016). If we assume that sentence comprehension is mediated by an activation-based model of cue-based retrieval, the performance of IWA can be explained by a combination of processing deficits, namely slow syntax and intermittent deficiencies.

Limitations and future directions

One important limitation of this work is the amount of data used for computational modeling. The data that we modeled in this paper (Pregla et al., 2021) is the largest-ever compilation of online measures for IWA in German. Nevertheless, the size of the IWA

group (21 subjects) remains relatively small when compared to the number of subjects tested in typical eye-tracking experiments with unimpaired participants. Unfortunately, collecting online data from impaired populations is extremely difficult, which is why most studies in the aphasia literature have a smaller number of participants. Usually, online experiments have 3 to 12 IWA and 10 to 20 control participants (e.g., Adelt et al., 2017; Burkhardt et al., 2003; Choy & Thompson, 2010; Dickey & Thompson, 2009; Engel et al., 2018; Hanne et al., 2015; Hanne et al., 2011; Love et al., 2008; Mack, Ji, & Thompson, 2013; Mack et al., 2016). An exception is the data presented in Caplan et al. (2013, 2015), with more than 50 IWA, although it does not include eye-tracking data.

The activation-based model outperforms the modified direct-access model in relative clauses, but both models perform similarly in pronoun resolution. We believe that the inability to find a clear answer in pronoun resolution has to do with the inherent limitations of the sample size, both in terms of subjects and items. Crucially, the relative clause experiment tested 40 items per subject (10 items per condition, 4 conditions), whereas the pronoun resolution tested 20 items per subject (10 items per condition, 2 conditions). Future work comparing these models will require much more data in order to distinguish between the models.

We have reported the most complex hierarchical structure that yielded converging fits, but in order to account for individual differences, an even more complex hierarchical structure would be necessary. This is especially true for the modified direct-access model, where an individual adjustment for the effect of δ would help in understanding the variability in the process of backtracking. The same holds for both models regarding the effect of fixations. In addition, this work focuses on average, group-level effects. While the comparisons between groups yield an estimate of the average performance, it has been shown that IWA have large within and between-subject variability (Mätzig et al., 2018; Patil, Hanne, et al., 2016; Pregla et al., 2021). A future direction is to develop an individual-level modeling approach, in which parameters are estimated for each subject, in

a similar vein to the modeling work in Mätzig et al. (2018) for offline data. Recent modeling work shows that under the cue-based retrieval, even among unimpaired participants, individual differences can modulate interference effects (Yadav, Paape, et al., 2021). Therefore, obtaining individual parameter estimates for IWA would be more informative regarding both interference effects, and the extent to which each processing deficit plays a role for each IWA.

A second limitation of this work concerns the implementation of the models. In order to compare the two competing models in a common architecture, we implemented simplified versions that focus on a single retrieval event. However, in order to account for sentence processing deficits in IWA across the whole trial, the models should include a parser. The original Lisp implementation of the activation-based model in ACT-R (Anderson et al., 2004; Lewis & Vasishth, 2005) includes a left-corner parsing algorithm that could conceivably be added to our model. However, as far as we are aware, there exists no computational implementation of a parser in the (modified) direct-access model. A future direction would be to incorporate a parser into the (modified) direct-access model, and to fit Bayesian versions of both models that account for individual parsing steps. This is especially challenging because it requires finding a common architecture that supports a parsing algorithm for both models, so that model comparisons can be performed.

Finally, another limitation concerns the use of looks to the target at the critical region as an index of retrieval. An analysis of eye fixation patterns across the entire trial would possibly be more informative regarding the time-course of interference during sentence processing. This is especially true for relative clauses, where our results show that higher fixations to the target at the critical region do not lead to faster reaction times in the picture selection task. Specific modeling techniques for visual-world-data could be considered, such as growth curve analysis (Mirman, 2017) or divergence point analysis (Stone, Lago, & Schad, 2020). Integrating these analyses with our computational modeling approach may be possible, and may yield important insights into the differences between

IWA and controls over the course of the trial.

Conclusion

We conducted the first large-scale evaluation of two computational models of sentence processing in individuals with aphasia (IWA) in German. Our study tested two competing models of cue-based retrieval – the activation-based model and a modified version of the direct-access model – against online and offline data from IWA and control participants. The data came from a visual-world eye-tracking experiment with a picture selection task. Similarity-based interference was manipulated in two linguistic constructions, namely pronoun resolution and relative clauses. Reaction times from the picture selection task were modeled as a function of interference, group (IWA versus control), lexical access speed, and fixations to the target picture at the critical region of the sentence. The results show that in pronoun resolution, IWA experience greater gender interference effects relative to control participants. In relative clauses, the data suggest that IWA exhibit a subject-object asymmetry, whereas controls do not. The effect of number interference in IWA seems to be overridden by the subject-object asymmetry, suggesting that in relative clauses, IWA may rely more strongly on case cues compared to number cues. The parameter estimates from both implemented models are in line with the slow syntax and the intermittent deficiencies accounts. In addition, the parameters of the modified direct-access model are also in line with the resource reduction theory. The cross-validation results show that while both models have a similar quantitative performance for the pronoun structures, the activation-based model outperforms the modified direct-access model in relative clauses.

Acknowledgements

This work was supported by the Deutsche Forschungsgemeinschaft (DFG) - Project-ID 317633480 - SFB1287, project B02 (PIs: Shravan Vasishth, Frank Burchert, and Nicole Stadie).

Declarations

Conflicts of interest

The authors have no relevant financial or non-financial interests to disclose.

Authors contributions

The first draft of the manuscript was written by Paula Lissón and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript. Data analysis and modeling was carried out by Paula Lissón and supervised by Shravan Vasishth and Dario Paape. Nicole Stadie, Frank Burchert and Dorothea Pregla contributed to the study conception and design. Material preparation, and data collection were performed by Dorothea Pregla.

Ethical Approval

Not applicable.

Consent to participate

Not applicable.

Consent to Publish

Not applicable.

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Appendix A

Details about the individuals with aphasia

Table A1, adapted from Pregla et al. (2021) shows a summary of the demographics and neurological information about the individuals with aphasia that took part in the experiments. More information about the participants and the experiments is available at Pregla et al. (2021) and Pregla et al. (2022).

Table A1

Demographic and neurological data of the individuals with aphasia that took part in the experiment, adapted from Pregla, Lissón, Vasishth, Burchert, and Stadie (2021). Note: Age and Education are given in years. T3 and T11 are part of the LEMO 2.0 (Stadie et al., 2013) battery of tests and the scores given in the table are raw scores; T3 (n=80) = auditory lexical decision, T11 (n=20) = auditory word-picture matching. IWA = individual with aphasia, P.O. = post onset, F = female, M = male, L = left, R = right, IMI = ischemic arteria cerebri media infarct, I = infarct, MA = arteria cerebri media aneurysm, VH = vertebrobasilar hemorrhage.

IWA	Gender	Age	Education	Years P.O.	Etiology	Localization	T3	T11	Aphasia type
2	F	72	8	7	IMI	L	77	19	Anomic
3	M	76	20	17	IMI	L/R	61	20	Not-classifiable
4	F	47	13	21	IMI	L	78	20	Anomic
6	M	55	14	10	IMI	L	67	20	Anomic
8	F	51	19	7	MA	L	74	20	Anomic
9	M	64	15	2	IMI	L	73	20	Anomic
10	M	58	18	1	IMI	L	52	20	Broca
11	F	63	12	1	IMI	L	73	20	Broca
12	F	46	12	13	IMI	L	65	20	Broca
13	M	74	13	8	IMI	L	57	20	Broca
14	M	66	13	17	IMI	L	75	20	Anomic
15	F	59	21	4	I	L	77	20	Broca
16	M	67	17	26	VH	R	72	19	Broca
17	F	43	14	10	IMI	L	65	20	Broca
18	M	57	13	1	I	L	67	18	Wernicke
19	F	52	19	8	IMI	L	76	20	Broca
20	M	38	13	3	IMI	L	73	19	Broca
21	M	57	18	2	IMI	L	66	18	Broca
22	F	67	16	5	IMI	L	76	20	Anomic
23	M	74	15	7	IMI	L	67	20	Anomic

Appendix B

Descriptive statistics

Pronoun

Figure B1. Descriptive statistics for the pronoun sub-experiment. The dots stand for the means, and the error bars show the standard error of the means. In the plot showing the fixations to the target picture at the critical region, the proportions are centered and scaled within groups.

Figure B2. Descriptive statistics for the relative clauses sub-experiment. The dots stand for the means, and the error bars show the standard error of the means. In the plot showing the fixations to the target picture at the critical region, the proportions are centered and scaled within groups.

Appendix C

Details about the computational implementations

For both the activation-based and the direct-access model, the varying intercepts and slopes for subject, $\mathbf{u}$, come from a multivariate normal distribution with x dimensions (where x = number of by-subject adjustments), abbreviated as MVN_x . The varying intercepts and slopes for items, $\mathbf{w}$, also come from a multivariate normal distribution with y dimensions, MVN_y (where y = number of by-item adjustments). In the equations below, $\mathbf{0}$ is a column vector of zeros with the x or y dimensions. The σ are the variance-covariance matrices of the multivariate normal distributions.

$$\mathbf{u} = MVN_x(\mathbf{0}, \Sigma_u) \quad \mathbf{w} = MVN_y(\mathbf{0}, \Sigma_w) \quad (1)$$

Activation-based model. For each trial i , values from two independent distributions are sampled, as shown in Equation (2). The lowest value becomes the estimated reaction time for trial i , see Equation (3).

Accumulator NP1

$$FT_{NP1_i} \sim \text{lognormal}(\mu_1, \sigma) \quad (2)$$

Accumulator NP2

$$FT_{NP2_i} \sim \text{lognormal}(\mu_2, \sigma)$$

$$RT_i = \min(FT_{NP1_i}, FT_{NP2_i}) \quad (3)$$

The hierarchical structure in the location parameter of the lognormal distribution for

each accumulator (μ_1 and μ_2) and in the standard deviation (σ) is shown in Equation (4).

Accumulator NP1

$$\begin{aligned}\mu_{NP1} = & \alpha_1 + u_{\alpha_1} + w_{\alpha_1} + (\beta_1 + w_{\beta_1}) \cdot group + \\ & (\beta_3 + u_{\beta_3}) \cdot condition + \beta_5 \cdot group \cdot condition + \\ & \beta_7 \cdot LDT + \beta_9 \cdot group \cdot LDT + \\ & \beta_{11} \cdot fixations + \beta_{13} \cdot fixations \cdot group\end{aligned}$$

Accumulator NP2

$$\begin{aligned}\mu_{NP2} = & \alpha_2 + u_{\alpha_2} + w_{\alpha_2} + (\beta_2 + w_{\beta_2}) \cdot group + \\ & (\beta_4 + u_{\beta_4}) \cdot condition + \beta_6 \cdot group \cdot condition + \\ & \beta_8 \cdot LDT + \beta_{10} \cdot group \cdot LDT + \\ & \beta_{12} \cdot fixations + \beta_{14} \cdot fixations \cdot group\end{aligned}\tag{4}$$

Noise parameter

$$\sigma = \sigma_0 + \beta_{15} \cdot group$$

In addition to the adjustments shown in Equation (4), in the model for relative clauses the following fixed effects were also added to both accumulators: RC type, RC type $\times$ condition, RC type $\times$ group, RC type group $\times$ group $\times$ condition, fixations $\times$ RC type, fixations $\times$ group $\times$ RC type. The slope for the effect of RC type also had a by-subject adjustment. Equation (5) shows the priors used in the activation-based model, all in log space.

$$\begin{aligned}\alpha_{1,2} & \sim normal(7.5, 0.6) \\ \beta_{1,\dots,15} & \sim normal(0, 0.5) \\ \sigma_0 & \sim normal_+(0, 0.5)\end{aligned}\tag{5}$$

Direct-access model. In Equation (6) the parameter θ stands for the probability of retrieval of the target; μ is the location of the distribution from which the reaction times

are sampled. P_b is the probability of backtracking, δ is the cost of backtracking (in log ms), and σ is the noise parameter. In addition to the adjustments shown in (6), in the model for relative clauses, the following fixed effects were added to θ : RC type, RC type $\times$ condition, RC type $\times$ group, and RC type $\times$ group $\times$ condition. The slope for the effect of RC type also had a by-subject adjustment.

$$\begin{aligned}
\mu &= \mu_0 + u_{\mu_0} + w_{\mu_0} + \beta_1 \cdot group \\
\theta &= \alpha + u_{\alpha} + w_{\alpha} + \beta_2 \cdot LDT + \beta_3 \cdot LDT \cdot group \\
&\quad (\beta_4 + w_{\beta_4}) \cdot group + (\beta_5 + u_{\beta_5}) \cdot condition + \\
&\quad \beta_6 \cdot group \cdot condition + \beta_7 \cdot fixations + \\
&\quad \beta_8 \cdot group \cdot fixations \\
\theta_b &= \alpha_b + u_{\alpha_b} + \beta_9 \cdot group \\
P_b &= \gamma + u_{\gamma} + \beta_{10} \cdot group \\
\delta &= \delta_0 + \beta_{11} \cdot group \\
\sigma &= \sigma_0 + \beta_{12} \cdot group
\end{aligned} \tag{6}$$

Equation (7) shows the priors used in the direct-access model. The priors for α , α_b and γ are in logit space, the rest of priors are in log space.

$$\begin{aligned}
\alpha &\sim normal(1, 0.5) \\
\alpha_b &\sim normal(0, 1) \\
\beta_{1,...,12} &\sim normal(0, 0.5) \\
\mu_0 &\sim normal(7.5, 0.6) \\
\gamma &\sim normal(-1, 0.5) \\
\delta_0 &\sim normal(0, 1) \\
\sigma_0 &\sim normal(0, 0.5)
\end{aligned} \tag{7}$$

Appendix D

Model estimates (activation-based model)

Pronouns

Table D1

Model estimates for the fixed effects on μ_{NP1} and μ_{NP2} and corresponding credible intervals, backtransformed to ms.

Parameter	Estimate	95% CrI	Accumulator (μ)
Group	2006 ms	CrI: [1604, 2453] ms	NP1
Group	-797 ms	CrI: [-2459, 629] ms	NP2
Condition	310 ms	CrI: [193, 433] ms	NP1
Condition	-1478 ms	CrI: [-2820, -431] ms	NP2
Condition $\times$ group	199 ms	CrI: [81, 322] ms	NP1
Condition $\times$ group	1424 ms	CrI: [400, 2720] ms	NP2
LDT	836 ms	[539, 1152] ms	NP1
LDT	588 ms	[-621, 1811] ms	NP2
LDT $\times$ group	671 ms	[377, 973] ms	NP1
LDT $\times$ group	51 ms	[-1147, 1243] ms	NP2
Fixations	41 ms	[-77, 160] ms	NP1
Fixations	518 ms	[-141, 1212] ms	NP2
Fixations $\times$ group	96 ms	[-23, 219] ms	NP1
Fixations $\times$ group	251 ms	[-430, 949] ms	NP2

Relative clauses

Table D2

Model estimates for the fixed effects on μ_{NP1} and μ_{NP2} and corresponding credible intervals, backtransformed to ms.

Parameter	Estimate	95% CrI	Accumulator (μ)
Group	2348 ms	[1687, 3055] ms	NP1
Group	4057 ms	[3279, 4916] ms	NP2
RC type	2417 ms	[2076, 2807] ms	NP1
RC type	-1897 ms	[-2372, -1459] ms	NP2
Condition	-68 ms	[-262, 122] ms	NP1
Condition	-228 ms	[-506, 40] ms	NP2
Condition $\times$ group	-37 ms	[-224, 153] ms	NP1
Condition $\times$ group	86 ms	[-180, 355] ms	NP2
RC type $\times$ group	-1670 ms	[-2019, -1366] ms	NP1
RC type $\times$ group	1847 ms	[1443, 2293] ms	NP2
Condition $\times$ RC type	-150 ms	[-323, 19] ms	NP1
Condition $\times$ RC type	631 ms	[385, 884] ms	NP2
Condition $\times$ RC type $\times$ group	103 ms	[-68, 276] ms	NP1
Condition $\times$ RC type $\times$ group	-249 ms	[-491, -10] ms	NP2
LDT	779 ms	[243, 1337] ms	NP1
LDT	812 ms	[252, 1398] ms	NP2
LDT $\times$ group	-50 ms	[-594, 496] ms	NP1
LDT $\times$ group	-460 ms	[-1045, 121] ms	NP2
LDT $\times$ RC type	-5 ms	[-258, 255] ms	NP1
LDT $\times$ RC type	19 ms	[-347, 385] ms	NP2
LDT $\times$ RC type $\times$ group	5 ms	[-251, 262] ms	NP1
LDT $\times$ RC type $\times$ group	291 ms	[-72, 677] ms	NP2
Fixations	-37 ms	[-205, 130] ms	NP1
Fixations	289 ms	[61, 521] ms	NP2
Fixations $\times$ group	-46 ms	[-211, 118] ms	NP1
Fixations $\times$ group	57 ms	[-173, 285] ms	NP2
Fixations $\times$ RC type	69 ms	[-97, 235] ms	NP1
Fixations $\times$ RC type	-27 ms	[-248, 204] ms	NP2
Fixations $\times$ RC type $\times$ group	75 ms	[-96, 244] ms	NP1
Fixations $\times$ RC type $\times$ group	-111 ms	[-341, 112] ms	NP2