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EMPIRICAL STUDY

MOSAIC+: A Crosslinguistic Model of Verb-Marking Errors in Typically Developing Children and Children With Developmental Language Disorder

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Abstract: This study extended an existing crosslinguistic model of verb-marking errors in children's early multiword speech (MOSAIC) by adding a novel mechanism that defaults to the most frequent form of the verb where this accounts for a high proportion of forms in the input. Our simulations showed that the resulting model not only provides a better explanation of the data on typically developing children but also captures the crosslinguistic pattern of verb-marking error in children with developmental language

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disorder, including the tendency of English-speaking children to show higher rates of optional-infinitive errors and the tendency of Dutch-, German-, and Spanish-speaking children to show higher rates of agreement errors. The new version of MOSAIC thus provides a unified crosslinguistic model of the pattern of verb-marking errors in typically developing children and children with developmental language disorder.

Keywords optional infinitives; crosslinguistic; developmental language disorder; child language; language development; defaulting

Introduction

Explaining the pattern of verb-marking errors in typically developing (TD) children and the pattern of verb-marking deficit in children with developmental language disorder (DLD) is a key challenge for theories of language acquisition. Verb-marking errors are a characteristic feature of the speech of TD children. For example, in many languages, young children make errors—often referred to as optional-infinitive errors—in which they use infinitives and other nonfinite verb forms in contexts in which a finite verb form is required. Deficits in verb marking are a characteristic feature of DLD. For example, English-speaking children with DLD tend to produce optional-infinitive errors over a longer period of time than do TD children and at higher rates than do controls matched for mean length of utterance (MLU). However, both the pattern of verb-marking errors in TD children and the pattern of verb-marking deficits in children with DLD vary across languages.

MOSAIC (model of syntax acquisition in children) is a computational model of language learning that simulates the developmental patterning of verb-marking errors across several different languages through the interaction of edge-based biases in learning with the distributional properties of the input language. MOSAIC simulates differences in the rate of optional-infinitive errors in Dutch, French, German, and Spanish. However, in its current form, it cannot simulate either the very high rates of optional-infinitive errors in English-speaking children or the crosslinguistic pattern of verb-marking deficits in children with DLD.

In this study, we supplemented MOSAIC's basic learning mechanism with a mechanism that defaults to the most frequent form of the verb when the relative frequency of that form in the input is above a certain threshold. We investigated whether this new version of the model (MOSAIC+) provided both a better explanation of the crosslinguistic data on TD children and a means of simulating the crosslinguistic pattern of deficits in children with DLD. Our simulations showed that MOSAIC+ can simulate both the very high rates of optional-infinitive errors in early child English and the fact that English-speaking children with DLD tend to show significantly higher rates of optional-infinitive errors than do MLU-matched controls, whereas Dutch- and German-speaking children do not, tending instead to show elevated, though still relatively low, rates of agreement and positioning errors.

Background Literature

The Optional-Infinitive Phenomenon

Verb-marking errors are a characteristic feature of children's early language. For example, between the ages of 2 and 4 years, English-speaking children often make errors like those in Examples 1a and 1b in which these children used a zero-marked form in a context that required a third-person singular present tense form (examples taken from the Manchester corpus; Theakston et al., 2001).

Example 1
a. *This go there (Anne, 2;6.04)
b. *And the lorry go on top (Warren, 2;7.05)

Early analyses of these kinds of errors assumed that they reflected incomplete knowledge of the target inflection (e.g., Brown, 1973) or the dropping of the inflection due to performance limitations in production (e.g., Bloom, 1990). However, crosslinguistic analyses (e.g., Wexler, 1994) showed that, in languages other than English, the equivalent errors tend to include verb forms marked with an infinitival morpheme like those in Examples 2a and 2b.

Example 2
Dutch
a. **Mama radio aan doen* (Peter, 2;0.07; Bol, 1996)
Mummy radio on put-INF (INF = infinitive)
"Mummy put radio on"
German
b. **Oma Brücke bauen* (Leo, 2;2.01; Behrens, 2006)
Grandma bridge build-INF
"Grandma build bridge"

Since these errors do not involve the use of a bare stem, they cannot be explained in terms of inflection drop, and this led to the view that the pattern of verb-marking errors across languages (including the incorrect use of zero-marked forms in English) reflects the use of infinitives and other nonfinite forms in finite contexts. These kinds of errors are typically referred to as optional-infinitive errors (Wexler, 1994), and the period during which they occur as the optional-infinitive stage.

Most research on the optional-infinitive stage has been conducted within a linguistic nativist framework. However, in a series of papers, we have used a computational model of language development (MOSAIC) to show that the crosslinguistic patterning of optional-infinitive errors can be understood as input-driven learning (see Pine et al., 2020, for a review). Below we outline the key features of MOSAIC. Appendix S1 in the online Supporting Information provides a more extended description of the model (including model architecture and learning mechanisms).

MOSAIC

MOSAIC is an unsupervised learning model that learns from input in the form of orthographically transcribed child-directed speech. MOSAIC gradually builds a network of words and strings of words from the input to which it has been exposed and produces output in the form of utterances that become progressively longer as learning proceeds. Some of these utterances are produced by rote, that is, have occurred as utterances or parts of utterances in the input. Others are produced generatively by substituting distributionally similar words into frames that have occurred as utterances or parts of utterances in the input. Since the average length of MOSAIC's output increases with learning, MOSAIC can be used to simulate developmental changes in children's speech as a function of increasing MLU.

A key feature of MOSAIC is that it is subject to a strong utterance-final bias in learning. Early versions of MOSAIC (Freudenthal et al., 2006, 2007, 2009) learned entirely from the right edge of the utterance; the model could only encode a word or phrase when everything that followed that word or phrase in the utterance had already been encoded in the network. MOSAIC thus built up its representation of an utterance by starting at the end of the utterance and slowly working its way to the beginning. This mechanism, which implements a recency effect in learning, can be likened to a moving window or buffer. Whenever an unknown word or word transition is encountered, the contents of the buffer are emptied, and only the most recently encountered word is left as a target for encoding. For example, when first exposed to the utterance *He goes home*, the model is only able to encode the word *home*. The word *goes* only becomes a target for encoding if the model has already encoded the word *home*, and the phrase *goes home* only becomes a target for encoding if the model has already encoded the words *goes* and *home*.

This utterance-final bias had the effect of restricting the strings that MOSAIC was able to produce to utterance-final sequences that had occurred in the input (or generative utterances based on such sequences). The current version of the model (Freudenthal et al., 2015) supplements MOSAIC's utterance-final bias with a (smaller) utterance-initial bias or left-edge learning mechanism. Left-edge learning works in a similar way to right-edge learning, except that it is anchored at the left edge of the utterance and restricted to a single word. MOSAIC now builds up its representation from both edges of the utterance and is subject to a (small) primacy and a (larger) recency effect in learning. MOSAIC also combines the products of right- and left-edge learning by associating utterance-initial and utterance-final elements based on their co-occurrence in utterances in the input. For example, MOSAIC now represents strings such as *He go home* by learning to associate utterance-initial words such as *He* and utterance-final phrases such as *go home* based on their co-occurrence in utterances such as *He can go home*.

The addition of left-edge learning and a mechanism for associating the products of right- and left-edge learning has the effect of expanding the range of strings that the model can produce to include strings with missing utterance-internal elements. This mechanism has the potential to result in concatenations of elements with implausibly long intervening sequences such as *Jason (the boy you met at playgroup) plays football*. These are avoided by making the probability of associating utterance-initial and utterance-final elements dependent on the distance between the elements. It also has the potential to generate nonchild-like concatenations such as *The (girl is going) to play football*. These are avoided by restricting concatenations to utterance-initial and utterance-final elements that are anchored at both edges of utterances in the input. That is, utterance-initial words can be concatenated only if they have also occurred in utterance-final position, and utterance-final elements can be concatenated only if the first word in the element has occurred in utterance-initial position.

MOSAIC simulates optional-infinitive errors because of the way it learns from the edges of the utterance and associates the products of right- and left-edge learning. This results in the production of partial utterances that have been present as utterance-final phrases in the input and as concatenations of utterance-initial words and utterance-final strings. The structures in the input that give rise to optional-infinitive errors are compound-finite structures: utterances that contain a finite modal or other auxiliary and an infinitive such as the English utterance *This could go there* or the German utterance *Oma kann die Brücke bauen* "Grandma can the bridge build-INF." The truncation of utterances like these results in subjectless optional-infinitive errors such as *go there* and *Brücke bauen* "bridge build-INF." The concatenation of utterance-initial words and utterance-final phrases from such utterances results in optional-infinitive errors with subjects such as *This go there* or *Oma Brücke bauen* "Grandma bridge build-INF."

MOSAIC simulates the developmental patterning of optional-infinitive errors because it learns to produce progressively longer utterances as a function of the amount of input to which it has been exposed. Children produce optional-infinitive errors at high rates early in their language development and produce fewer optional-infinitive errors as the length of their utterances increases. MOSAIC simulates this pattern because of the way that compound finites pattern in the relevant languages. In compound finites, the finite auxiliary precedes the infinitive. Since MOSAIC produces increasingly long utterance-final phrases, the short phrases it produces early on are likely to contain only nonfinite verb forms. As the phrases MOSAIC produces become longer, finite auxiliaries start to appear, and optional-infinitive errors are gradually replaced by the compound finites from which they have been learned.

It is worth emphasizing at this point that MOSAIC is a relatively simple distributional analyzer with no access to semantic information, which is clearly not powerful enough to acquire many aspects of adult syntax. MOSAIC is therefore best viewed as a simplified model of grammatical development that does not incorporate several variables that are known to affect children's language learning. Nevertheless, because of its ability to produce child-like utterances across a range of different languages, MOSAIC provides a powerful means of testing hypotheses about the relation between crosslinguistic variation in children's early language and crosslinguistic differences in the language to which they are exposed.

In an early paper, Freudenthal et al. (2007) showed that a right-edge learning model that learned optional-infinitive errors from both questions and declaratives could simulate variation in the developmental patterning of optional-infinitive errors across Dutch, German, and Spanish and the developmental patterning of optional-infinitive errors with third-person singular subjects in English. Freudenthal et al. also showed that the key variable was the way that MOSAIC's utterance-final bias interacted with the relative frequency of nonfinite and finite verbs in utterance-final position—high in Dutch, moderately high in German, and low in Spanish, as are children's respective rates of optional-infinitive errors in these languages. In a later paper, Freudenthal et al. (2009) showed that the same version of MOSAIC could simulate semantic-conditioning effects including the modal reference effect and the eventivity constraint—the fact that in many languages optional-infinitive errors tend to have a modal meaning and to be restricted to eventive rather than stative verbs, and the absence or reduced size of these effects in English. In a more recent paper, Freudenthal et al. (2015) showed that a version of the model that distinguished between declaratives and questions in the input and learned from both edges of the utterance could simulate the crosslinguistic patterning of optional-infinitive errors in declaratives and wh-questions in English, Dutch, German, and Spanish.

However, Freudenthal et al. (2010) also showed that MOSAIC suffers from one important weakness as an account of the crosslinguistic data: It is unable to explain the very high rate of optional-infinitive errors in English at low MLUs. Freudenthal et al. compared MOSAIC with Legate and Yang's (2007) variational learning model—a probabilistic parameter setting model which also has the potential to explain differences in the rate of optional-infinitive errors across languages. More specifically, they investigate how well the two models predict the rate and lexical patterning of optional-infinitive errors at an MLU of approximately 2 in English, Dutch, German, French, and Spanish. Their results provided support for MOSAIC's account of optional-infinitive errors in the form of significant correlations between the rate at which children produced optional-infinitive errors on particular verbs and the rate at which those verbs occurred in compound-finite as opposed to simple-finite structures in child-directed speech in all five languages studied. However, they also showed that, although both MOSAIC and the variation learning model were good at predicting differences in the rate of optional-infinitive errors in Dutch, German, French, and Spanish, neither was able to predict the very high rate of optional-infinitive errors in English. Freudenthal et al. (2010) therefore argued for a model of verb-marking error in which some errors reflect the use of infinitives learned from compound-finite structures in the input and others reflect a process of defaulting to the most frequent form of the verb when the target form is only weakly represented in a child's system. Such a model would predict particularly high rates of optional-infinitive errors in English, where the most frequent form of the verb is usually the bare stem and where bare-stem errors are indistinguishable from optional-infinitive errors.

Supplementing MOSAIC With a Frequency-Sensitive Defaulting Mechanism

An extended version of MOSAIC that supplements the model's basic learning mechanisms with a frequency-sensitive defaulting mechanism has several potential advantages as an account of the crosslinguistic pattern of verb-marking errors. First, adding some degree of frequency-sensitivity to the model's output has the potential to explain a wider range of errors and is consistent with a wealth of evidence that frequency at a variety of levels not only increases fluency and protects items from error, but can also result in errors in which low-frequency items are replaced by higher-frequency words and sequences (see Ambridge et al., 2015, and Divjak & Caldwell-Harris, 2015, for reviews). Thus, although in many languages the most common type of verb-marking error is the use of a nonfinite form in a finite context, there is evidence from more highly inflected languages that young children also make verb-marking errors in which they use the most frequent finite form of the verb in the wrong person/number context (Aguado-Orea & Pine, 2015; Engelmann et al., 2019; Räsänen et al., 2016; Rubino & Pine, 1998). A frequency-sensitive defaulting mechanism would provide a straightforward explanation of these kinds of errors.

Second, such a model has the potential to provide a better explanation of the rate of optional-infinitive/bare-stem errors in early child English. Thus, because the bare stem covers five of the six cells in the English present tense paradigm, defaulting errors in English are particularly likely to involve the use of the bare stem and, since the bare stem is indistinguishable from the infinitive, these errors will increase the rate of optional-infinitive errors. In fact, there is already evidence that at least some apparent optional-infinitive errors in English reflect frequency-sensitive defaulting. For example, in an elicited production study, Räsänen et al. (2014) found a significant relationship between children's tendency to use bare forms of particular verbs in third-person singular present tense contexts and the relative frequency with which these verbs occur as bare forms versus third-person singular forms in finite present tense contexts in English child-directed speech. Moreover, Kueser et al. (2018) has since replicated this result in a group of English-speaking children with DLD and in a group of MLU-matched controls.

Third, such a model has the potential to explain the crosslinguistic pattern of verb-marking deficit in children with DLD. DLD, also referred to in the literature as specific language impairment, refers to a significant deficit in language ability that cannot be attributed to hearing loss or neurological damage (see Leonard, 2014, for a review). Although children with DLD are not a homogeneous population, deficits in verb-marking are a characteristic feature of the disorder. However, the pattern of verb-marking deficits in DLD varies across languages. Thus, English-speaking children with DLD tend to produce optional-infinitive/bare-stem errors at higher rates than do MLU-matched controls, even at high MLUs (Kueser et al., 2018; Rice et al., 1995). However, this effect appears to be specific to English. For example, Wexler et al. (2004) found no such differences in the rate of optional-infinitive errors in their Dutch-speaking sample at an MLU of 3 and an MLU of 4, and, although Rice et al. (1997) did find an MLU-matching effect at an MLU of 2.66 in their German sample, this effect had disappeared by the time their MLU had reached 3.77.

In contrast, several researchers have found higher rates of subject–verb agreement and verb-positioning errors in Dutch and German. For example, both de Jong (1999) and Wexler et al. (2004) reported elevated (though still relatively low) rates of agreement error in Dutch-speaking children with DLD; Clahsen et al. (1997) reported higher rates of agreement error in German-speaking children with DLD; and a number of researchers have reported verb-positioning errors in both Dutch (de Jong, 1999; Wexler et al., 2004) and German (Clahsen et al., 1997; Hamann et al., 1998; see Leonard, 2014, for a review). These positioning errors typically involve the incorrect use of finite forms (which are restricted to second position in Dutch and German) in utterance-final position, though the incorrect use of infinitives in second position has also been reported.

Taken together, these findings have suggested that it might be possible to simulate the crosslinguistic pattern of verb-marking deficit in DLD by changing the defaulting threshold in an extended version of MOSAIC. Increasing the rate of defaulting by reducing the threshold at which defaulting errors occur was likely to increase the rate of optional-infinitive/bare-stem errors in English. However, it would likely increase the rates of agreement and verb-positioning errors in Dutch and German, where the most frequent form of the verb is likely to be a finite form that is readily distinguishable from the infinitive and restricted to second position in main clauses.

The Present Study

The aim of our study was to investigate whether an extended version of MOSAIC that supplemented MOSAIC's basic learning mechanism with a novel defaulting mechanism provided both (a) a better explanation of the crosslinguistic data on TD children and (b) a means of simulating the crosslinguistic pattern of verb-marking deficits in children with DLD. In a first set of simulations, we investigated the extent to which adding a defaulting mechanism to MOSAIC improved the model's ability to simulate differences in the rate of optional-infinitive errors in English, Dutch, German, and Spanish at an MLU of 2. In a second set of analyses, we investigated how this defaulting mechanism interacted with the frequency statistics of child-directed speech in the four languages to result in different levels of defaulting and different types of defaulting error. In a final set of simulations, we investigated whether increasing the rate of defaulting errors by reducing the defaulting threshold in the model allowed us to simulate the crosslinguistic pattern of differences in the rate of optional-infinitive, agreement, and verb-positioning errors in children with DLD relative to MLU-matched controls.

Method

In our study, we implemented MOSAIC+ by combining the version of MOSAIC described above and in Appendix S1 with a novel defaulting mechanism that we applied to the model's output. In this section, we first describe the way in which we ran simulations in MOSAIC, then the novel defaulting mechanism, and finally the way in which we manipulated defaulting rates in the simulations that followed.

Running MOSAIC Models

MOSAIC is trained by feeding an input corpus through the model multiple times. This is necessary because the child-directed speech samples available in the languages modeled are typically not large enough to support gradual learning. Learning in MOSAIC is slow, and MOSAIC initially represents just a few short utterance-final phrases. As learning proceeds, MOSAIC represents more phrases that extend further to the left of the utterance as well as utterance-initial words, some of which have been associated with utterance-final phrases to form concatenations. Output is generated from MOSAIC by producing all the utterance-final phrases and concatenations of utterance-initial words and utterance-final phrases that it represents. Output from MOSAIC thus consists of a corpus of utterances that can be directly compared to corpora of child-directed speech. Since the average length of MOSAIC's output increases with increased training, it can also be matched to children in different stages of development based on their MLU in words.

For the current simulations, we trained MOSAIC on the child-directed speech from Anne and Becky's transcripts from the English Manchester corpus (Theakston et al., 2001), the child-directed speech from Matthijs and Peter's transcripts from the Dutch Groningen corpus (Bol, 1996), the child-directed speech from the German Leo corpus (Behrens, 2006), and the child-directed speech from Juan's transcripts from the Spanish OreaPine corpus (Aguado-Orea & Pine, 2015). These are the same corpora that Freudenthal et al. (2010) used in their comparison of MOSAIC and the variation learning model. As in Freudenthal et al. (2010), we used versions of the English input corpora that were coded for the occurrence of verbs in third-person singular contexts (e.g., *That goes-3SG there*; *She can go-3SG home*; *He is going-3SG out*, where 3SG = third-person singular). This feature allows for the identification of verbs that are learned from/produced in third-person singular contexts even when no subject is present and thus allows for a meaningful comparison of optional-infinitive error rates in English and in the other languages where optional-infinitive errors can be readily identified even when the subject is absent.

The Novel Defaulting Mechanism

We implemented defaulting in the model by identifying the most frequent form of each verb in a large corpus of child-directed speech in each language and by substituting this form for lower-frequency forms of the same verb in MOSAIC's output if its proportional frequency exceeded a certain threshold. We implemented defaulting deterministically rather than probabilistically. That is, we always made changes when the proportional frequency of the relevant form exceeded the threshold and never made changes when proportional frequency did not exceed the threshold. Our implementing defaulting in this way did not reflect a theoretical commitment to deterministic defaulting but rather an attempt by us to keep the defaulting mechanism as simple as possible to make it easier to understand the effects of manipulating the model's tendency to default across the different languages. The setting of the defaulting threshold was inevitably somewhat arbitrary. In the simulations of children's speech at an MLU of 2, we explored the use of values of .60, .65, and .70. We chose these values to restrict defaulting to verb forms that made up a relatively large proportion of the relevant instances of that verb in the input while at the same time leaving scope for increasing the defaulting threshold as a function of increasing MLU in the later simulations. In our simulations of the speech of TD children and children with DLD at an MLU of 3 and an MLU of 4, we used values of .85 and .95 for the TD models and .65 and .75 for the DLD models. We chose these values to allow us to distinguish clearly between the TD and DLD models while at the same time allowing us to increase the thresholds used in both sets of models as a function of increasing MLU.

We collected verb counts from both declarative and interrogative input utterances. However, since MOSAIC assumes that children represent progressively longer utterance-final strings, we based the defaulting counts used at different MLUs not on corpus-wide statistics but on utterance-final strings matched to the model's MLU. Thus, we based defaulting counts for models at an MLU of 3 on utterance-final strings of up to three words and based defaulting counts at an MLU of 4 on utterance-final strings of up to four words. We also computed corpus-wide statistics for the purpose of comparison. This allowed us to investigate the extent to which defaulting is affected by imposing a similar utterance-final bias on the defaulting mechanism to MOSAIC's utterance-final bias in learning. To maximize the reliability of our defaulting counts, we used corpora larger than the child-specific corpora used in the actual simulations. These were, for English, the combined input for the 12 children of the Manchester corpus (Theakston et al., 2001: ~350,000 utterances); for Dutch, the combined input for the eight children of the Groningen corpus (Bol, 1996: ~80,000 utterances); for German, the child-directed speech of the dense Leo corpus (Behrens, 2006: ~240,000 utterances); and for Spanish, the input for the two children from the OreaPine corpus (Aguado-Orea & Pine, 2015) and the 50 children from the Fern-Aguado corpus (~120,000 utterances combined). These corpora are all available in the CHILDES database (MacWhinney, 2000).

Defaulting Counts

Since defaulting is assumed to reflect competition between finite forms of the verb, we restricted defaulting counts to finite lexical verbs and, for the sake of simplicity, to present tense verb forms. However, since in English, Dutch, and German the infinitive is homophonous with one of the present tense forms, we also included infinitives in the counts when they occurred in a finite utterance (e.g., *He can go there*, *Does he like that?*) and the finite auxiliary was not part of the relevant utterance-final string. This allowed us to investigate how defaulting interacts with MOSAIC's utterance-final bias in learning. In English, Dutch, and German, we identified finite utterances by searching the input for subject pronouns and a relevant verb form in an appropriate position. For Spanish, which allows null subjects, we used the Mor (morphology) tier of the transcripts. This procedure allowed for the exclusion of verbs in imperative contexts.

In order to facilitate the collection of defaulting counts for utterance-final strings of different lengths, we marked present tense verbs in simple-finite contexts as tensed (e.g., *He goes*-tensed *to school*, *They go*-tensed *home*), while we left unmarked the forms in imperative contexts (e.g., *Go home*). This made it possible for us to distinguish the two forms of *go* when analyzing two-word utterance-final strings—*go*-tensed *home* contributed to the counts for *go*, while *go home* was ignored. We marked infinitives that occurred in a compound-finite context (e.g., *He can go there*, *Does he go home?*) as modal, while we marked the finite auxiliary as tensed (*e.g., He can*-tensed *go*-modal *there*, *Does*-tensed *he go*-modal *home?*). Forms marked as modal contributed to the counts for the relevant verb, provided the tensed auxiliary was not part of the

Table 1 Present tense paradigm for the verb *run* in English, Dutch, German, and Spanish

Verb form	English	Dutch	German	Spanish
Infinitive	Run	Rennen	Rennen	Correr
1st-person singular	I run	Ik ren	Ich renne	Corro
2nd-person singular	You run	Jij rent [a]	Du rennst	Corres
3rd-person singular	She runs	Zij rent	Sie rennt	Corre
1st-person plural	We run	Wij rennen	Wir rennen	Corremos
2nd-person plural	You run	Jullie rennen	Ihr rennt	Corréis
3rd-person plural	They run	Zij rennen	Sie rennen	Corren

Note. [a] In Dutch (but not German), the second-person singular suffix *–t* is omitted in questions; the resultant form is a bare stem that is homophonous with the first-person singular form, therefore boosting the frequency of this form in the input.

relevant utterance-final string. That is, the infinitive form of *go* in *Does*-tensed *he go*-modal *home?* contributed to the counts for *go* in two- and three-word utterance-final strings but not in four-word utterance-final strings. We designed this procedure to simulate children's increasing sensitivity to the fact that, in compound-finite contexts, tense is marked on the auxiliary rather than on the lexical verb.

Table 1 illustrates the present tense verb paradigm in English, Dutch, German, and Spanish using the verb *run*, which is regular in all four languages. The Spanish example does not include pronouns because Spanish is a pro-drop language. Table 1 shows that the English present tense paradigm comprises two forms, one of which matches the infinitive, that the Dutch paradigm comprises three forms, one of which matches the infinitive, that the German paradigm comprises four forms, one of which matches the infinitive, and that the Spanish paradigm comprises six forms, none of which matches the infinitive. Since the defaulting counts collapse across matching forms, this means that, all other things being equal, defaulting is likely to be most pervasive in English and least pervasive in Spanish, with Dutch and German falling somewhere in between. However, since defaulting is applied on a verb-by-verb basis, it is also possible that different verbs default to different forms. For example, English verbs that tend to occur in third-person singular contexts (e.g., *fits*) may default to the third-person singular form.

Table 2 illustrates the basic word-order patterns of the four different languages. It can be seen that finite lexical verbs usually occur before their complements in all four languages. However, the infinitive in compound-finite

Table 2 Examples of simple-finite and compound-finite constructions in English, Dutch, German, and Spanish

Language	Construction
Simple-finite	
English	I drink coffee
Dutch	Ik drink koffie “I drink-FIN coffee”
German	Ich trinke Kaffee “I drink-FIN coffee”
Spanish	Bebo café “(I) drink-FIN coffee”
Compound-finite	
English	I want to drink coffee
Dutch	Ik wil koffie drinken “I want-FIN coffee drink-INF”
German	Ich moechte Kaffee trinken “I want-FIN coffee drink-INF”
Spanish	Quiero beber café “(I) want-FIN drink-INF coffee”

Note. FIN = finite; INF = infinitive.

structures occurs before its complements in English and Spanish and after its complements in Dutch and German, where it is tied to utterance-final position. This results in infinitives being more common than finite forms in utterance-final position in Dutch and German, which means that, in these languages, defaulting is likely to interact with MOSAIC’s utterance-final bias in learning such that the model is more likely to default to the infinitive at low MLUs—when verb counts are drawn from short utterance-final strings—and more likely to default to a finite form at high MLUs. It also means that defaulting has the potential to result in verb-positioning errors in these languages since defaulting from a finite form to an infinitive results in an infinitive that precedes its complement and defaulting from an infinitive to a finite form results in a finite form that follows its complement.

Defaulting in MOSAIC’s Output

We applied defaulting counts to MOSAIC’s output by searching the relevant output file for the occurrence of verb forms considered in the child-directed speech analysis and substituting default forms (e.g., forms that made up more than 65% of the relevant forms in the input) for nondefault forms. Thus, the output utterance *he eats*-3SG was changed to *he eat*-3SG if *eat* had been identified as the default form of the verb *eat*. Likewise, the utterance *they fit there* was changed to *they fits there* if *fits* had been identified as the default form of the verb *fit*. The only exceptions to this rule were instances where an infinitive verb form occurred in an utterance with a tensed auxiliary (e.g., *can fit there*). We left these utterances unchanged even if we had identified *fits* as the default form because these utterances already contained a tensed form. That is, in line with the input analysis (where the phrase *can*-tensed *go*-modal *away* did not contribute to the counts for *go* if the modal verb *can* was included in the relevant utterance-final string), we assumed that, as utterance-length increases, children become increasingly sensitive to the fact that, in compound-finite contexts, tense is marked on the auxiliary rather than on the lexical verb and tensed verb forms are not substituted for untensed verb forms in compound-finite constructions. This mechanism prevented the model from producing errors such as *kann rent* and *can runs* but still allowed the model to produce positioning errors in Dutch and German by substituting tensed verb forms (e.g., *drink*, *drinkt*) for infinitives (e.g., *drinken*) in utterances from which the tensed auxiliary was absent (e.g., *koffie drinken* → **koffie drinkt*).[1]

Analysis Plan

In this article, we have reported three sets of simulations and analyses. The first set of simulations (Study 1) focused on the extent to which adding a defaulting mechanism to MOSAIC improved the model's ability to simulate differences in the rate of optional-infinitive errors in English, Dutch, German, and Spanish at an MLU of 2. The second set of analyses (Study 2) focused on how the novel defaulting mechanism interacted with the frequency statistics of child-directed speech in the four languages to result in different levels of defaulting and different types of defaulting errors. The third set of simulations (Study 3) focused on whether it was possible to capture the crosslinguistic pattern of differences in the rate of OI, agreement, and verb-positioning errors in children with DLD relative to MLU-matched controls by changing the model's defaulting threshold. We conducted all statistical analyses in R (R Core Team, 2021).

Study 1: Simulating Crosslinguistic Variation in the Rate of Optional-Infinitive Errors at a Mean Length of Utterance of 2

In these simulations, we investigated the extent to which adding a defaulting mechanism to MOSAIC improved the model's ability to simulate the rate of optional-infinitive errors in English, Dutch, German, and Spanish at an MLU of 2. We did this by comparing the output of models in the absence of defaulting with the output of models after we had applied defaulting with the defaulting threshold set to .60, .65, and .70 in each of the four languages. We analyzed the output in the same way as Freudenthal et al. (2010) had done by distinguishing between utterances that contained only a nonfinite verb form (e.g., *rennen* in Dutch and *run*-3SG, *running*-3SG in English) and utterances that contained at least one finite verb form (e.g., *rent* and *kan rennen* in Dutch

Table 3 Rate of optional-infinitive (OI) errors in MOSAIC's output at mean length of utterance (MLU) = 2 for models trained on English (Anne, Becky), Dutch (Matthijs, Peter), German (Leo), and Spanish (Juan) together with the proportions for the corresponding children

Child	MLU	OI errors: Child	OI errors: Model	Number of utterances with verbs in model's output
Anne	2.04	.87	.57	99
Becky	2.00	.97	.59	60
Matthijs	2.10	.77	.65	719
Peter	2.06	.74	.65	680
Leo	1.97	.58	.57	1,236
Juan	2.01	.20	.12	824

and *runs*-3SG, *can run*-3SG and *is running*-3SG in English). The dependent variable (proportion of optional-infinitive errors) was the number of utterances in the first category divided by the sum of the utterances in the first and second category. Appendix S2 in the Supporting Information online provides further details of the coding scheme.

Rates of Optional-Infinitive Errors in MOSAIC in the Absence of Defaulting

Table 3 shows the rate of optional-infinitive errors in MOSAIC's output in the absence of defaulting together with the corresponding rates for the children on whose input the models were trained, as reported by Freudenthal et al. (2010). It is clear from Table 3 that MOSAIC substantially underestimated the proportion of optional-infinitive errors in early child English (by 30% for Anne and 38% for Becky). These results replicated those of Freudenthal et al. (2010) and showed that, while MOSAIC's edge-based learning mechanism was sufficient to capture differences in the rate of optional-infinitive errors across Dutch, German, and Spanish, it could not capture the very high level of optional-infinitive errors in early child English.

Rates of Optional-Infinitive Errors in MOSAIC With Defaulting Based on Utterance-Final Statistics

Table 4 shows the rate of optional-infinitive errors in MOSAIC's output after defaulting at thresholds of .60, .65, and .70 based on utterance-final words and two-word strings. These data suggested that defaulting using utterance-final statistics resulted in a better fit to the child data than we had obtained using

Table 4 Rate of optional-infinitive (OI) errors in MOSAIC's output at mean length of utterance (MLU) = 2 for models trained on English (Anne, Becky), Dutch (Matthijs, Peter), German (Leo), and Spanish (Juan) input with defaulting at thresholds of .60, .65, and .70 based on utterance-final words and two-word strings (rate of affected utterances in parentheses)

Child	MLU	OI errors: Child	OI errors: Model threshold = .60	OI errors: Model threshold = .65	OI errors: Model threshold = .70
Anne	2.04	.87	.91 (.34)	.91 (.34)	.80 (.23)
Becky	2.00	.97	.85 (.28)	.85 (.28)	.83 (.27)
Matthijs	2.10	.77	.70 (.08)	.70 (.08)	.70 (.08)
Peter	2.06	.74	.72 (.09)	.72 (.09)	.71 (.08)
Leo	1.97	.58	.60 (.08)	.59 (.06)	.59 (.05)
Juan	2.01	.20	.12 (.04)	.12 (.03)	.12 (.02)

the previous version of the model, with differences in the defaulting threshold having little effect on the overall pattern of results.

We confirmed this by running arcsine transformations on the child and model rates reported in Tables 3 and 4 and computing Pearson correlations (with Bayes factors). This analysis revealed a marginally significant correlation between the child and model rates for the old version of the model ($r = .808$, $p = .052$, $BF = 1.84$, indicating inconclusive support for the hypothesized relation), and significant correlations for each of the new versions of the model ($r = .948$, $p = .004$; $r = .950$, $p = .004$; and $r = .962$, $p = .002$) with Bayes factors of 3.76, 3.81, and 4.23, respectively, all indicating moderate support for the hypothesized relation. A comparison of the data in Tables 3 and 4 revealed that the improvement in fit was mainly due to a substantial increase in the rate of optional-infinitive errors in English (of 34% for Anne's model and 26% for Becky's model). However, it also reflected a smaller increase in the rate of optional-infinitive errors in Dutch (of 5% for Matthijs's model and 7% for Peter's model), with the rate of optional-infinitive errors in German and Spanish being largely unaffected. These results showed that combining MOSAIC's utterance-final bias with a mechanism that defaulted to the most frequent form of the verb provided a better explanation of the crosslinguistic data.

Rates of Optional-Infinitive Errors in MOSAIC With Defaulting Based on Corpus-Wide Statistics

Table 5 shows the rate of optional-infinitive errors in MOSAIC's output after defaulting at thresholds of .60, .65, and .70 based on utterance-final strings of

Table 5 Rate of optional-infinitive (OI) errors in MOSAIC's output at mean length of utterance (MLU) = 2 for models trained on English (Anne, Becky), Dutch (Matthijs, Peter), German (Leo), and Spanish (Juan) with defaulting at thresholds of .60, .65, and .70 based on utterance-final strings of up to 10 words in length (rate of affected utterances in parentheses)

Child	MLU	OI errors: Child	OI errors: Model threshold = .60	OI errors: Model threshold = .65	OI errors: Model threshold = .70
Anne	2.04	.87	.69 (.27)	.68 (.26)	.67 (.24)
Becky	2.00	.97	.67 (.33)	.70 (.30)	.70 (.30)
Matthijs	2.10	.77	.49 (.22)	.49 (.21)	.52 (.15)
Pet	2.06	.74	.52 (.17)	.52 (.18)	.54 (.12)
Leo	1.97	.58	.51 (.08)	.51 (.06)	.52 (.06)
Juan	2.01	.20	.12 (.04)	.12 (.03)	.12 (.02)

up to 10 words in length—effectively based on a corpus-wide analysis. These data were interesting because they suggested that defaulting using corpus-wide statistics resulted in a poorer fit to the child data than did defaulting using utterance-final statistics. This was partly because it resulted in a much less pronounced increase in the rate of optional-infinitive errors in English—increase of 11% for both Anne and Becky's models compared to 34% and 26%, respectively, for the previous models. However, it was also because it resulted in a decrease in the rate of optional-infinitive errors in Dutch and German (of 16% for Matthijs's model, 13% for Peter's model, and 6% for Leo's model). This reduction in the fit to the Dutch and German data was not particularly surprising since, in both languages, although the infinitive was the most common form of the verb in utterance-final position, it was not the most common form of the verb in the input as a whole. However, it did underline the need to link defaulting to the model's utterance-final bias in learning to explain the crosslinguistic data. That is, it suggested that it is necessary to assume that the same utterance-final bias that shaped the development of the model's representations also affected its sensitivity to the relative frequency of different verb forms in the input.

In summary, the simulations presented above showed that adding a defaulting mechanism to MOSAIC allowed the model to simulate the very high rate of optional-infinitive errors in early child English without affecting the model's previously good fit to the data on Dutch, German and Spanish. However, the simulations also showed that this was only the case when we had based the defaulting counts on utterance-final phrases matched to the model's MLU. The simulations therefore underlined the important role

Table 6 Rate of verbs that would default to a particular form of the verb in English at different maximum string lengths

String length	Bare form	3rd-person singular	No default	Number of verbs
1	.94	.01	.06	108
2	.96	.01	.03	181
3	.94	.02	.04	215
5	.89	.05	.07	213
10	.82	.06	.12	195

Table 7 Rate of verbs that would default to a particular form of the verb in Dutch at different maximum string lengths

String length	Infinitive (stem + –*en*)	1st-/2nd- person singular (stem)	2nd-/3rd- person singular (stem + –*t*)	No default	Number of verbs
1	.82	.05	.04	.09	78
2	.57	.14	.09	.20	93
3	.39	.20	.09	.31	99
5	.12	.26	.14	.49	101
10	.00	.36	.19	.46	101

played by MOSAIC's utterance-final bias in explaining the developmental data.

Study 2: Defaulting as a Function of the Statistics of Child-Directed Speech in the Four Languages

In these analyses, we investigated how the defaulting mechanism interacted with the frequency statistics of child-directed speech in the four languages. We did this by setting the defaulting parameter to .65 and exploring the pattern of defaulting and the rate of affected verbs for defaulting counts based on utterance-final strings of different lengths in the child-directed speech corpora. Tables 6–9 show the results of these analyses for each of the four languages. We have expressed the results as the rate of verbs that would be subject to defaulting on the basis of a threshold of .65. We have shown the results for utterance-final words and utterance-final strings of two, three, five, and 10 words. We have included complete utterances in string sets that exceeded their length. Since utterances of more than 10 words in length are rare in child-directed speech, the analysis of 10-word utterance-final strings is, in effect, a corpus-wide analysis.

Table 8 Rate of verbs that would default to a particular form of the verb in German at different maximum string lengths

String length	Infinitive (stem + *–en*)	1st-person singular (stem + *–e*)	2nd-person singular (stem + *–st*)	3rd-person singular (stem + *–t*)	No default	Number of verbs
1	.79	.00	.02	.08	.12	168
2	.63	.03	.02	.12	.21	196
3	.49	.02	.01	.16	.31	229
5	.21	.03	.03	.21	.53	265
10	.10	.04	.04	.28	.55	283

Table 9 Rate of verbs that would default to a particular form of the verb in Spanish at different maximum string lengths

String length	Infinitive	1st-person singular	2nd-person singular	3rd-person singular	No default	Number of verbs
1	.15	.02	.03	.17	.63	147
2	.10	.01	.02	.15	.71	163
3	.07	.01	.02	.21	.70	179
5	.04	.01	.02	.21	.72	189
10	.04	.01	.02	.25	.68	193

Table 6 presents the results for the English input analysis. It is clear from these data that most English verbs defaulted to the bare form (i.e., occurred as a bare form in over 65% of tensed contexts). Fewer verbs defaulted to the bare form in longer strings. This was because untensed forms in compound structures contributed to the counts for short but not for longer strings, which more likely included both a tensed auxiliary and an untensed lexical verb (e.g., *That might*-tensed *go*-modal *there*).

Nevertheless, even in the 10-word string analysis, more than 80% of verbs defaulted to the bare form. This reflected the fact that, in English, zero-marked forms like *I go* and *you go* are far more frequent than overtly tensed forms like *he goes*, and explains why adding a defaulting mechanism to the model had such a profound effect on the rate of optional-infinitive errors in English. It also suggested that allowing the model to default at high MLUs (based on statistics from longer utterance-final strings) may be an effective way of simulating the higher rate of optional-infinitive errors in English-speaking children with DLD relative to MLU-matched controls. This is because defaulting based on statistics from longer utterance-final strings increased the rate of optional-infinitive errors in the model's output without affecting the model's MLU.

Tables 7 and 8 present the results for the Dutch and German analyses. It is clear from these data that fewer verbs defaulted to the infinitive in Dutch and German than defaulted to the bare form in English, regardless of string length. However, it is also clear that the most common default form in Dutch and German changed as string length increased. The infinitive form stem + *–en* was the most common default for utterance-final words and two- and three-word strings, but for longer strings the first- and second-person singular stem in Dutch and the third-person singular stem + *–t* in German were the most common defaults. This pattern reflected the SOV/V2 (subject–object–verb/verb second) nature of Dutch and German, where nonfinite forms (including the infinitive) take utterance-final position, whereas finite forms take second position (i.e., V2) and precede their complements. Nonfinite forms are therefore more likely to occur in short utterance-final strings, while finite forms are more likely to occur in longer strings.

The fact that fewer Dutch and German verbs showed a strong preference for the infinitive explained why the model's defaulting mechanism had less effect on the rate of optional-infinitive errors in Dutch and German than it did in English; the fact that the pattern of preference changed as a function of string length explained why it was necessary to link defaulting to the model's utterance-final bias in learning in order to explain the Dutch and German data. However, these differences between Dutch and German and English also suggested that allowing the model to default at high MLUs—based on statistics from longer utterance-final strings—is likely to have a different effect in Dutch and German than it does in English. This is because, in Dutch and German, it is likely to result in the replacement of low-frequency finite forms with high-frequency finite forms rather than the replacement of finite forms with infinitives—as is the case in English. It may therefore provide a way of simulating the fact that, in contrast to English-speaking children with DLD, Dutch- and German-speaking children with DLD tend to produce agreement and verb-positioning errors rather than optional-infinitive errors at high MLUs.

Table 9 presents the results for the Spanish input analysis. We have not included plural forms in the table because there were no verbs that defaulted to a plural verb form at any string length. Compared to Dutch and German, the pattern in Spanish was relatively stable. Most verbs were not subject to defaulting, regardless of string length. However, 15% to 25% defaulted to the third-person singular form. This pattern of defaulting was likely to result in the replacement of low-frequency finite forms with high-frequency third-person singular forms rather than the replacement of finite forms with infinitives and explained why the model's defaulting mechanism had so little effect on the rate of optional-infinitive errors in Spanish. It was also consistent with the pattern of verb-marking error that has been reported in early child Spanish, in which children tend to make agreement errors at relatively low rates, most of which involve the inappropriate use of third-person singular forms. Finally, this pattern of defaulting suggested that allowing the model to default at high MLUs based on statistics from longer utterance-final strings simply prolonged the period during which agreement errors were made. This finding is broadly consistent with the data on verb-marking error in Spanish-speaking children with DLD who have tended to show slightly higher rates of agreement error relative to age-matched, but not to MLU-matched controls (Bedore & Leonard, 2001).

In summary, the input analyses that we have presented above revealed that English verbs showed an overwhelming preference for the bare form and, this was consistent across different string lengths. Fewer verbs showed a strong preference in Dutch and German, and the preferred form changed as a function of string length. In short strings, there tended to be a preference for the infinitive, which occurred in utterance-final position; in longer strings, there tended to be a preference for finite forms, which occurred in V2. Even fewer verbs showed a strong preference in Spanish, but where they did, this tended to be a preference for the third-person singular form. These input analyses therefore explained why defaulting had a large effect on the rate of optional-infinitive errors in English, a smaller effect in Dutch and German, and virtually no effect in Spanish. The analyses also suggested that defaulting at higher MLUs tended to increase the rate of optional-infinitive errors in English, but not in Dutch, German, or Spanish, where it was likely to result in defaulting to the highest frequency finite form and hence to agreement and positioning errors rather than optional-infinitive errors.

Study 3: Simulating the Crosslinguistic Pattern of Verb-Marking Error in Children With Developmental Language Disorder

In the simulations for Study 3, we investigated the model's ability to capture the crosslinguistic pattern of verb-marking error in TD children and children with DLD. We did this by applying different defaulting thresholds to the output from each of the children's models at an MLU of 3 based on utterance-final strings of up to three words and at an MLU of 4 based on utterance-final strings of up to four words. The thresholds for the models with DLD were .65 and .75, respectively. The thresholds for the TD models were .85 and .95, respectively. Since a lower defaulting threshold resulted in higher levels of defaulting error, we chose these values to obtain higher levels of defaulting in the DLD than in the TD models and decreasing levels of defaulting as a function of MLU. We calculated rates of optional-infinitive errors in the same way as in the first set of analyses. We calculated rates of agreement error by identifying cases in which defaulting led to the substitution of one finite form for another (e.g., *rent* for *ren* in Dutch and *runs* for *run* in English) and dividing the number of such cases by the total number of simple-finite contexts. We calculated rates of verb-positioning errors in Dutch and German by identifying cases in which defaulting led to the substitution of an infinitive into a finite context and cases in which defaulting led to the substitution of a finite form into an infinitival

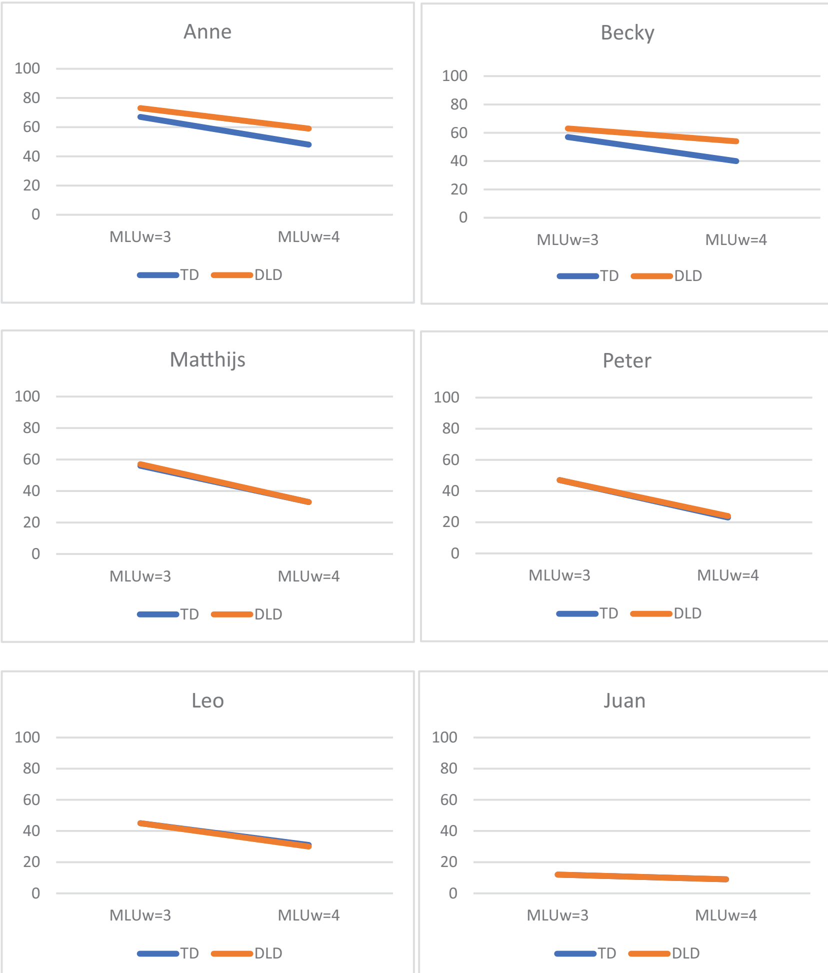

Figure 1 Percentage of optional infinitive errors for each typically developing (TD) model and the equivalent model with a lower defaulting threshold: developmental language disorder (DLD). Raw data are provided in Appendix S3 in the Supporting Information online. MLUw = mean length of utterance (words)wileyonlinelibrary.com

context. In each case, the denominator was the sum of the number of such cases and the number of correctly placed infinitives or finite forms.

Figure 1 shows the rates of optional-infinitive errors and Figure 2 shows the rates of agreement errors in each TD model and the equivalent model with

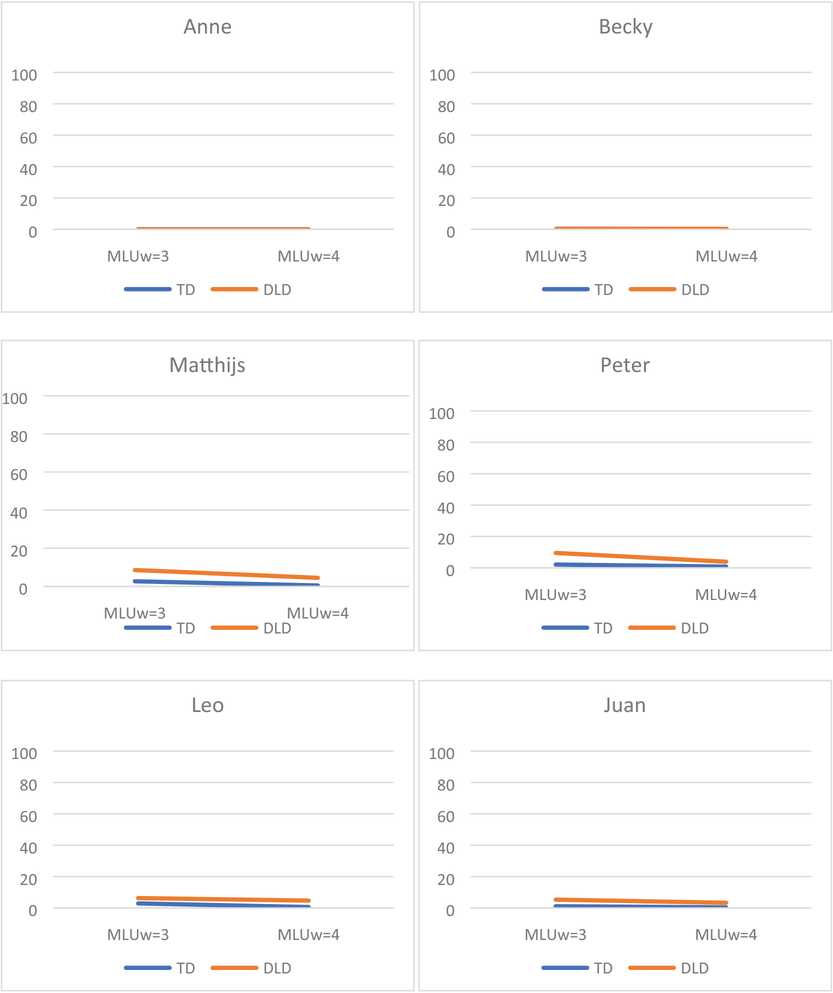

Figure 2 Percentage of agreement errors for each typically developing (TD) model and the equivalent model with a lower defaulting threshold: developmental language disorder (DLD). Raw data are provided in Appendix S3 in the Supporting Information online. MLUw = mean length of utterance (words). wileyonlinelibrary.com

a lower defaulting threshold (DLD). Figure 1 suggests that reducing the defaulting threshold at higher MLUs did have an effect on the rate of optional-infinitive errors in the English models, resulting in increases of 6% at an MLU of 3 and 11% and 14% at an MLU of 4 but had little or no effect on the rate of optional-infinitive errors in the Dutch, German, and Spanish models.

We analyzed these data by running a mixed-effects Poisson regression model with a random effect of modeled-child on the intercept, fixed effects of error (optional-infinitive error, optional-infinitive correct), model type (TD, DLD), language (English, non-English), and MLU (3, 4), plus all two-way interactions of error, model type, and language and the critical three-way interaction of error, model type, and language. We coded all binary variables as -0.5 and 0.5. All fixed effects were significant (see Appendix S3 in the Supporting Information online), including the critical three-way interaction of error, model type, and language, $b = 0.46$, 95% CI = [0.38, 0.53], $SE = 0.04$, $z = 12.20$, $p < .001$, which indicated that the difference in the relative frequency of optional-infinitive errors versus correct utterances was greater in the English DLD versus TD models than in the non-English DLD versus TD models (where it was essentially zero). Importantly, a model including the three-way interaction gave a better fit than any submodel (ΔAIC = 146.52 for the next best model).[2]

These results confirmed that reducing the defaulting threshold at high MLUs allowed the model to simulate the increased rate of optional-infinitive errors relative to MLU-matched controls that we had found in English-speaking children with DLD but not seen in Dutch-, German-, and Spanish-speaking children. In the Spanish models, this was a straightforward consequence of the fact that defaulting to the infinitive was extremely rare. In Dutch and German, it reflected the fact that, although some verbs did still default from a finite to the infinitive form at high MLUs, other verbs defaulted in the opposite direction, cancelling out any potential increase.

Figure 2 suggests that, in contrast to the increase in optional-infinitive rates in the English models, reducing the defaulting threshold at higher MLUs in the Dutch, German, and Spanish models resulted in increased rates of agreement errors. These increases were seen in all three languages at both MLU points. However, they resulted in relatively low overall error rates (never greater than 10%). This pattern was also consistent with the crosslinguistic literature on DLD, which has reported elevated, but still relatively low, rates of agreement errors in Dutch-, German-, and Spanish-speaking children.

We analyzed these data by running a mixed-effects Poisson regression model on the non-English data, with a random effect of modeled-child on the intercept, fixed effects of error (agreement error, agreement correct), model type (TD, DLD), and MLU (3, 4), and the critical two-way interaction of error and model type. We coded all binary variables as -0.5 and 0.5. All fixed effects were significant (see Appendix S3), including the critical two-way interaction of error and model type, $b = 1.60$, 95% CI = [1.47, 1.73], $SE = 0.07$, $z = 24.39$, $p < .001$, which indicated that the difference in the relative frequency of agreement errors versus correct utterances was greater in the DLD than in the TD models. Importantly, a model including the two-way interaction gave a better fit than any submodel (ΔAIC = 778.58 for the next best model).

Finally, as we noted earlier, defaulting in Dutch and German has the potential to result in positioning errors in which infinitives occur in V2 and finite forms occur in inappropriate utterance-final contexts. Table 10 reports the rates at which such errors occurred in the Dutch and German models. It can be seen from these data, that although positioning errors were relatively rare (ranging from 0% to 2.1% in the TD models and 2.0% to 6.4% in the DLD models), they were more common in the DLD than in the TD models at both MLU points.

We analyzed these results by running separate mixed-effects Poisson regression models with random effects of modeled-child on the intercept, fixed effects of error (positioning error, positioning correct), model type (TD, DLD), and MLU (3, 4), plus the critical two-way interaction of error and model type. In both models, all fixed effects were significant (see Appendix S3), including the critical two-way interactions of error and model type, $b = 1.82$, 95% CI = [1.58, 2.07], $SE = 0.13$, $z = 14.50$, $p < .001$, and $b = 1.71$, 95% CI = [1.45, 1.97], $SE = 0.13$, $z = 12.87$, $p < .001$, indicating that the difference in the relative frequency of positioning errors and correct utterances was greater in the DLD models. Importantly, models including these two-way interactions gave a better fit than any submodels (ΔAICs = 294.91 and 28.63 for the next best models). These results were consistent with the literature on child Dutch and German, where positioning errors have been found to be rare in TD children, particularly at high MLUs, but to occur at elevated, though still relatively low, rates in children with DLD. The results thus provided further support for the idea that a model in which defaulting occurs at different rates in impaired and unimpaired children provides a plausible account of the crosslinguistic pattern of verb-marking error in TD children and in children with DLD.

In summary, modeling the verb-marking deficit in DLD in terms of an increased tendency to default to the most common form of the verb captured both the tendency of English-speaking children with DLD to produce optional-infinitive errors at higher rates than MLU-matched controls and the tendency of Dutch-, German-, and Spanish-speaking children with DLD to show problems with subject–verb agreement, and Dutch- and German-speaking children to show problems with verb placement. It thus suggested that MOSAIC+ has the potential to explain both the crosslinguistic pattern of verb-marking error in

Table 10 Rates of positioning errors in the Dutch (Matthijs and Peter) and German (Leo) models and the equivalent models with a lower defaulting threshold (developmental language disorder)

Model	Finites in final position	Finites in V2	Percent error	Infinitives in V2	Infinitives in final position	Percent error
Mathijs (MLU = 3)	10	817	1.2	15	1,396	0.1
Mathijs-DLD (MLU = 3)	46	761	5.7	46	1,381	3.2
Mathijs (MLU = 4)	4	2,164	0.2	0	1,571	0
Mathijs-DLD (MLU = 4)	54	2,105	2.5	32	1,550	2.0
Peter (MLU = 3)	8	1,306	0.6	33	1,536	2.1
Peter-DLD (MLU = 3)	82	1,209	6.4	74	1,497	4.7
Peter (MLU = 4)	18	2,983	0.6	0	1,304	0
Peter-DLD (MLU = 4)	58	2,897	2.0	76	1,268	5.7
Leo (MLU = 3)	17	2,881	0.6	17	2,871	0.6
Leo-DLD (MLU = 3)	79	2,776	2.8	72	2,850	2.5
Leo (MLU = 4)	18	6,081	0.3	3	3,463	0.1
Leo-DLD (MLU = 4)	130	6,059	2.1	67	3,342	2.0

Note. V2 = verb in second position; MLU = mean length of utterance; DLD = developmental language disorder.

TD children and the crosslinguistic pattern of verb-marking deficit in children with DLD.

Discussion

The aim of our study was to investigate whether a model which supplements MOSAIC's basic learning mechanism with a mechanism that defaults to the most frequent form of the verb provides both a better explanation of the crosslinguistic data for TD children and a means of simulating the crosslinguistic pattern of verb-marking deficit for children with DLD. In a first set of analyses, we investigated the extent to which adding a defaulting mechanism to MOSAIC improved the model's ability to explain the crosslinguistic pattern of optional-infinitive errors in TD children at an MLU of 2. Our results showed that the addition of a defaulting mechanism allowed MOSAIC to simulate the very high rate of optional-infinitive errors in early child English without affecting the model's previously good fit to the data on Dutch, German, and Spanish. These findings are consistent with the idea that at least some apparent optional-infinitive errors in English reflect a process of defaulting to the most frequent form of the verb (Kueser et al., 2018; Räsänen et al., 2014) and suggest that the very high rate of optional-infinitive errors in English reflects the fact that, in English, but not in the other languages, defaulting tends to result in the same kind of errors as the learning of infinitives directly from the input.

In a second set of analyses, we investigated how the novel defaulting mechanism interacted with the frequency statistics of child-directed speech in the four languages across utterance-final strings of different lengths. The results of these analyses showed that defaulting is likely to result in bare-stem errors in English and third-person singular errors in Spanish regardless of string length. However, they also showed that defaulting is likely to result in different kinds of errors in Dutch and German, depending on the length of the utterance-final strings on which defaulting counts are based. Thus, defaulting based on short utterance-final strings is likely to result in optional-infinitive errors and infinitives in V2, whereas defaulting based on longer utterance-final strings is likely to result in agreement errors and finite forms in utterance-final position. These findings showed that defaulting can explain why English-speaking children tend to make bare-stem errors in their speech, whereas Spanish children tend to make third-person singular errors. They also showed why it is necessary to allow defaulting to interact with MOSAIC's utterance-final bias in learning to explain the Dutch and German data at an MLU of 2. The reason is that defaulting based on corpus-wide statistics reduces the rate of optional-infinitive errors in the model's output by reducing the number of infinitives and increasing the number of finite forms. Finally, they suggest that defaulting based on the statistics of longer utterance-final strings tends to result in different patterns of error in English than in Spanish, Dutch, and German, with bare-stem errors being the most common type of error in English and agreement errors being the most common type of error in Spanish, Dutch, and German.

In a final set of analyses, we manipulated the defaulting parameter in the model in order to simulate the crosslinguistic pattern of differences in the rate of optional-infinitive, agreement, and verb-positioning errors in TD children and in children with DLD. As is clear from our results, increasing the amount of defaulting at high MLUs by lowering the defaulting threshold allows the model to simulate the higher rate of optional-infinitive errors in English-speaking children with DLD and the absence of this effect in Dutch-, German-, and Spanish-speaking children. It also allows the model to simulate the increased rate of agreement errors in Dutch-, German-, and Spanish-speaking children with DLD and the increased rate of verb-positioning errors in Dutch- and German-speaking children. An important feature of these simulations is that, although the rates were significantly higher in the DLD than in the TD models, the rates of agreement and positioning errors were never unrealistically high (i.e., never greater than 10%). This feature of the data is a straightforward consequence of the use of a frequency-sensitive defaulting mechanism which, by its very nature, only results in defaulting errors when the target is a relatively low-frequency form of the verb. This tends to result in low overall error rates which hide higher error rates in low-frequency parts of the system. Interestingly, this is exactly the pattern of error that has been reported in detailed analyses of the speech of children learning more highly inflected languages (e.g., Aguado-Orea & Pine, 2015; Engelmann et al., 2019).

Overall, these findings suggest that a model in which defaulting occurs at different rates in impaired and unimpaired children provides a plausible account of the crosslinguistic pattern of verb-marking error in TD children and the crosslinguistic pattern of verb-marking deficits in children with DLD. They are also consistent with a wealth of evidence that, while frequency at both the word and sequence level can increase fluency and protect items from error, it can also result in errors in which low-frequency items are replaced by higher-frequency items (see Ambridge et al., 2015, for a review). The implication is that the verb-marking deficits in DLD reflect a system that is particularly susceptible to intrusions from high-frequency items.

Limitations and Future Research Directions

It is worth noting at this point that, since we implemented different levels of defaulting in our model by directly manipulating the defaulting parameter, our findings still leave unanswered the question of what underlying mechanism is responsible for the different levels of defaulting seen in TD children and in children with DLD. One possibility that maps more or less directly onto the way that we implemented defaulting in the current version of the model is that greater defaulting in DLD reflects a deficit in the ability to inhibit competition from higher-frequency forms (see McMurray et al., 2019, for an explanation of lexical deficits in DLD in terms of reduced lexical inhibition). A second possibility is that greater defaulting reflects a deficit in word learning and paradigm building. According to this view, greater defaulting reflects an underlying deficit in children's ability to learn low-frequency forms and morphological patterns that leaves those with DLD more susceptible to competition from high-frequency forms of the verb (see Harmon et al., 2023, for an account of deficits in past-tense marking along these lines). And a third possibility is that greater defaulting reflects a deficit in children's ability to process long-distance dependencies that differentiate between contexts that require lower- and higher-frequency forms. According to this view, children with DLD use the most frequent form of the verb because they have yet to distinguish between contexts that require a lower-frequency form of the verb (e.g., *Dolly sits there*) and contexts that require a higher-frequency form of the verb (e.g., *Does Dolly sit there?* or *We let Dolly sit there*). This leaves children with DLD susceptible to competition from higher-frequency forms of the verb for a longer period of time than is the experience of TD children (see Leonard et al., 2015, for a more detailed description of this competing sources of input account, and Freudenthal et al., 2021, for a model of the verb-marking deficit in DLD which shows how a deficit in the ability to take account of information in the preceding context interacts with the distributional properties of English and Spanish to result in a greater verb-marking deficit in English than in Spanish). Determining which of these mechanisms provides the most plausible account of the increased level of defaulting in DLD is clearly beyond the scope of our study; and given the multifaceted nature of DLD, it is possible that all of explanations may have some role to play. However, our research opens up a number of avenues for future research that have the potential to further increase understanding of the variables that underlie the verb-marking deficit in children with DLD.

Conclusion

This study shows that a new version of MOSAIC that defaults to the highest-frequency form of the verb can explain both the crosslinguistic pattern of optional-infinitive errors in TD children and the crosslinguistic pattern of verb-marking deficit in children with DLD. This model has several advantages over previous models of verb-marking errors. First, it can explain the very high rate of optional-infinitive errors in early child English. Second, it can explain why children learning languages other than English tend to make both optional-infinitive and agreement errors in their speech. Third, it can explain why English-speaking children with DLD produce optional-infinitive errors at higher rates than do MLU-matched controls, whereas children learning other languages tend to make more agreement and positioning errors.

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Notes

1 In fact, MOSAIC can also simulate errors like **koffie drinkt* and **Kaffee trinkt* through right-edge learning. This is because, although ungrammatical in main clauses in Dutch and German, such sequences are grammatical at the ends of utterances in subordinate clauses.

2 At the suggestion of a reviewer, we also ran Bayesian alternatives to all the reported frequentist mixed-effects Poisson regression models using the brms package in R employing default priors. In all cases the 95% confidence intervals for the critical interaction terms did not cross zero (see Appendix S3).

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Accessible Summary

Appendix S1. Extended Description of MOSAIC.

Appendix S2. Extended Description of the Coding Scheme for Optional-Infinitive Errors.

Appendix S3. Data and Results Tables for Mixed-Effects Poisson Regression Models.