MOSAIC+: a cross-linguistic model of verb-marking in typically developing children and
children with Developmental Language Disorder

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Abstract

This study extends an existing cross-linguistic model of verb-marking error in children's early multi-word 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 show that the resulting dual-factor model not only provides a better explanation of the data on typically developing (TD) children, but also captures the cross-linguistic pattern of verb-marking error in children with Developmental Language Disorder (DLD), including the tendency of English-speaking children to show higher rates of Optional Infinitive (OI) 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 cross-linguistic model of the pattern of verb-marking error in TD children and children with DLD.

1 Introduction

Explaining the pattern of verb-marking error 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 (OI) errors) in which they use infinitives and other non-finite 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 OI errors for longer than TD children and at higher rates than both age-matched and language-matched controls. However, both the pattern of verb-marking error in TD children and the pattern of verb marking deficit 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 in terms of the interaction between edge-based biases in learning and the distributional properties of the input language. MOSAIC simulates differences in the rate of OI errors in Dutch, French, German and Spanish. However, in its current form, it cannot simulate either the very high rates of OI errors in English-speaking children or the cross-linguistic pattern of verb-marking deficit in children with DLD.

In this study, we supplement 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 investigate whether this Dual-Factor Model provides both a better explanation of the cross-linguistic data on TD children and a means of simulating the cross-linguistic pattern of deficit in children with DLD. Our simulations show that this new version of MOSAIC can simulate both the very high rates of OI error in early

child English and the fact that English-speaking children with DLD tend to show significantly higher rates of OI errors at high MLUs than language-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.

1.1 The OI 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 (1) and (2) in which they use a zero-marked form in a context that requires a third person singular (3sg) present tense form (examples taken from the Manchester corpus; Theakston, Lieven, Pine & Rowland, 2001).

(1) *This go there (Anne, 2;6.4)

(2) *And the lorry go on top (Warren, 2;7.05)

Early analyses of these kinds of errors assumed that they reflect 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; Valian, 1991). However, cross-linguistic analyses (e.g., Wexler, 1994) have shown that, in languages other than English, the equivalent errors tend to include verb forms marked with an infinitival morpheme like those in (3) and (4).

Dutch

(3) *Mama radio aan doen. (Peter, 2;0.7; Bol, 1995)

Mummy radio on put-INF

Mummy put radio on

German

- (4) *Oma Brücke bauen. (Leo, 2;2.1; 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 has 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 non-finite forms in finite contexts. These kinds of errors are typically referred to as Optional Infinitive (OI) errors (Wexler, 1994), and the period during which they occur as the OI stage.

1.2 MOSAIC

The majority of research on the OI phenomenon has been conducted within a linguistic nativist framework. However, in a series of papers, Freudenthal and his colleagues have used a computational model of early language development (MOSAIC) to show that the cross-linguistic patterning of OI errors can be understood in terms of input-driven learning (see Pine, Freudenthal, & Gobet, 2020, for a review).

MOSAIC is a relatively simple distributional learning mechanism, which takes as input corpora of orthographically transcribed child-directed speech and produces as output utterances (both rote-learned and generative) that become progressively longer as learning proceeds. As a result of these characteristics, MOSAIC can be used to generate corpora of ‘child-like’ utterances at different ‘stages’ of development, and hence to model the speech of children learning different languages across a range of MLU values.

MOSAIC simulates OI errors because it has a strong utterance-final (and, in later work, edge-based) bias in learning. This bias results in the production of partial utterances that were present as utterance-final phrases in the input on which the model was trained and, in later work, utterance-final strings and concatenations of utterance-initial words or phrases and utterance-final strings. The structures in the input that give rise to OI errors are compound finite structures: utterances that contain a (finite) modal or 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 OI errors such as ‘go there’ and ‘Brücke bauen’. The concatenation of utterance-initial and utterance-final phrases from such utterances results in OI errors with subjects such as ‘This go there’ or ‘Oma Brücke bauen’ (Grandma bridge build-INF).

MOSAIC simulates the developmental patterning of OI 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 OI errors at high rates early in development and produce fewer OI 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 modal or auxiliary precedes the infinitive. Since MOSAIC produces increasingly long utterance-final phrases, the short phrases it produces early on are likely to contain only non-finite verb forms. As the phrases MOSAIC produces become longer, finite modals and auxiliaries start to appear, and OI errors are gradually replaced by the compound finites from which they have been learnt.

In an early paper, Freudenthal, Pine, Aguado-Orea, and Gobet (2007) showed that a version of MOSAIC that learned OI errors from both declaratives and questions could simulate variation in the developmental patterning of OI errors across Dutch, German and Spanish and the developmental patterning of OI errors with third person singular (3sg)

subjects in English. They also showed that the key factor was the way that MOSAIC's utterance-final bias interacted with the relative frequency of non-finite and finite verbs in utterance-final position (high in Dutch, moderately high in German and low in Spanish, as are children's rates of OI errors in the respective languages). In a later paper, Freudenthal, Pine, and Gobet (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 OI 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, Pine, Jones, and Gobet (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 cross-linguistic patterning of OI errors in declaratives and Wh- questions in English, Dutch, German and Spanish.

However, Freudenthal, Pine, and Gobet (2010) have also shown that MOSAIC suffers from one important weakness as an account of the cross-linguistic data: it is unable to explain the very high rate of OI errors in English at low MLUs. Freudenthal et al. (2010) compare MOSAIC with Legate and Yang's (2007) Variational Learning Model (VLM) — a probabilistic parameter setting model which also has the potential to explain differences in the rate of OI errors across languages. More specifically, they investigate how well the two models predict the rate and lexical patterning of OI errors at an MLU of approximately 2 in English, Dutch, German, French, and Spanish. Their results provide support for MOSAIC's account of OI errors in the form of significant correlations between the rate at which children produce OI errors on particular verbs and the rate at which those verbs occur in compound finite as opposed to simple finite structures in child-directed speech in all 5 of the languages studied. However, they also show that, although both MOSAIC and the VLM are good at predicting differences in the rate of OI errors in Dutch, German, French, and Spanish, neither

is able to predict the very high rate of OI errors in English. Freudenthal et al. therefore argue for a Dual-Factor 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 the child's system. Such a model would predict particularly high rates of OI errors in English, where the most frequent form of the verb is usually the bare stem, and where bare stem errors are indistinguishable from OI errors.

1.3 The Dual-Factor Model

The Dual-Factor Model has several potential advantages over MOSAIC as an account of the pattern of verb-marking error across languages. First, it has the potential to provide a better explanation of the rate of OI/bare stem errors in early child English. Thus, because the bare stem covers 5 of the 6 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 OI errors.

In fact, there is already some evidence that at least some apparent OI errors in English are defaulting errors of this kind. This evidence comes from an elicited production study by Räsänen, Ambridge, and Pine (2014) of young children's use of 3sg -s in present tense contexts. Räsänen et al.'s results show a significant relation between children's tendency to use bare forms of particular verbs in 3sg 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. This effect is difficult to explain under the assumption that all English-speaking children's uses of zero-marked forms in 3sg contexts are OI errors, and suggests that at least some of English-speaking children's verb-marking errors reflect a process of defaulting to the bare stem. Interestingly, this result has since been replicated by Kueser, Leonard, and Deevy (2018) in a group of English-speaking

children with DLD (with an average MLU of 4.08) and a group of MLU-matched controls. In the Kueser et al. study, although the children with DLD made significantly more errors than the TD children, both groups showed a significant input effect of the kind reported by Räsänen et al. (2014).

Second, the Dual-Factor Model has the potential to explain a wider range of verb-marking errors than MOSAIC. Thus, although in many languages the most common type of verb-marking error is the use of a non-finite form in a finite context, there is evidence from more highly inflected languages that young children sometimes make verb-marking errors in which they use the most frequent finite form of the verb in the wrong person/number context. For example, in a case study of a child learning Brazilian Portuguese, Rubino, and Pine (1998) found that, while the rate of errors in 3sg contexts was only 0.5%, the rate of error in third person plural contexts was 43.5%, with most errors involving the use of the higher frequency 2sg/3sg form. Similarly, in a study of two children learning Castilian Spanish, Aguado-Orea and Pine (2015) found the same pattern in both of the children's early production data (0.7% vs. 33.9% for Juan and 0.7% vs. 46.4% for Lucía), with most errors involving the use of the higher frequency 3sg form (see also Räsänen, Ambridge, & Pine, 2016, and Engelmann, Kolak, Granlund, Szreder, Ambridge, Pine, Theakston, & Lieven, 2019, for evidence that young children make the same kind of errors in Finnish and Polish). Some generativist researchers (e.g., Salustri & Hyams, 2003; Grinstead, De la Mora, Vega-Mendoza, & Flores, 2009) have argued that these kinds of verb-marking errors can be seen as analogous to OI errors. However, this interpretation cannot explain why children learning the relevant languages produce both OI errors and subject-verb agreement errors during the early stages, whereas this is exactly what the Dual-Factor Model would predict.

Third, the Dual-Factor Model has the potential to explain the cross-linguistic pattern of verb-marking deficit in children with DLD. DLD, also referred to in the literature as specific

language impairment (SLI), 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 deficit in DLD varies across languages. Thus, as we have already seen, English-speaking children with DLD tend to produce OI/bare stem errors at higher rates than language-matched controls, even at high MLUs (Kueser et al., 2018; Rice, Wexler, & Cleave, 1995; Rice, Wexler, & Hershberger, 1998). However, this effect appears to be specific to English. For example, Wexler, Schaeffer, and Bol (2004), found no such differences in the rate of OI errors in their Dutch-speaking sample at MLU=3 and MLU=4, and, although Rice, Noll, and Grimm (1997) did find an MLU-matching effect at MLU=2.66 in their German sample, this effect had disappeared by MLU=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) report elevated (though still relatively low) rates of agreement error in Dutch-speaking children with DLD; Clahsen, Bartke, and Göllner (1997) report higher rates of agreement error in German-speaking children with DLD (see also Rothweiler, Chilla, & Clahsen, 2012); 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; Hamman, Penner, & Lindner, 1998; List & Pine, in press; Roberts & Leonard, 1997; 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 suggest that it might be possible to simulate the cross-linguistic pattern of verb-marking deficit in DLD by changing the defaulting threshold in a

Dual-Factor Model. Increasing the rate of defaulting by reducing the threshold at which defaulting errors occur is likely to increase the rate of OI/bare stem errors in English.

However, it is likely to 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.

1.4 The Present Study

In view of these considerations, the aim of the present study is to investigate whether a Dual Factor Model which supplements MOSAIC's basic learning mechanism with a novel defaulting mechanism provides both (a) a better explanation of the cross-linguistic data on TD children and (b) a means of simulating the cross-linguistic pattern of verb-marking deficit in children with DLD. In a first set of simulations, we investigate the extent to which adding a defaulting mechanism to MOSAIC improves the model's ability to simulate differences in the rate of OI errors in English, Dutch, German, and Spanish at MLU=2. In a second set of analyses, we investigate how this defaulting mechanism interacts 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 investigate whether increasing the rate of defaulting errors by reducing the defaulting threshold in the model allows us to simulate the cross-linguistic pattern of differences in the rate of OI, agreement and verb-positioning errors in children with DLD relative to MLU-matched controls.

2 General Method

In the present paper, the Dual-Factor model was implemented by combining the version of MOSAIC used in Freudenthal et al. (2010, 2015), with a novel defaulting mechanism that was applied to the model's output. We therefore start by describing MOSAIC, and the way in which simulations are run in MOSAIC, and then describe the novel defaulting mechanism

and the way in which defaulting rates were manipulated in the simulations that follow. An extended description of MOSAIC can be found in Appendix A in the materials section.

2.1 MOSAIC

MOSAIC is a relatively simple unsupervised learning mechanism that learns from input in the form of orthographically transcribed child-directed speech. The model represents utterances as string of words and produces output in the form of ‘utterances’ that become progressively longer as a function of learning, and can hence be compared with those of language learning children at different points in development. MOSAIC builds up its representation of the input to which it is exposed incrementally, and employs a strong utterance-final bias – learning is initially restricted to the right edge of the sentence, and the phrases MOSAIC represents will gradually extend further to the left. Since the average length of MOSAIC’s output increases with learning, MOSAIC can be used to simulate developmental changes in children’s speech by comparing child and model output across a range of MLU values.

MOSAIC simulates the developmental patterning of OI errors because of the way in which MOSAIC networks are built. In earlier versions of MOSAIC (Freudenthal et al., 2006, 2007, 2009), networks were built solely through right-edge learning, and the model was therefore only able to produce utterance-final strings. These versions of MOSAIC did not distinguish between declarative and interrogative input, and OI errors with subjects (e.g., *He go home*) were simulated by truncating questions to the right of the modal or auxiliary verb (e.g., ~~Can~~ *he go home?*). The version of MOSAIC used in the current paper is the version described in Freudenthal et al. (2010, 2015) implemented in a new more efficient algorithm¹. This version

¹In earlier versions of the model, MOSAIC was implemented as a discrimination net. The current version of the model uses hash tables, which speeds up the running of MOSAIC models considerably.

of the model distinguishes between declarative and interrogative input and combines the original right-edge learning mechanism with a more limited form of left-edge learning. The model's output consists of utterance-final phrases and concatenations of utterance-initial and utterance-final phrases, which the model has learned to associate. This allows the model to learn OI errors with subjects (e.g., *He go home*) from declarative input, as concatenations from which the auxiliary or modal verb appears to have been omitted (e.g., *He ~~can~~ go home*). It also allows the model to learn OI errors in Wh- questions (e.g., *Where he go?*) from interrogative input (e.g. *Where ~~does~~ he go?*), and hence to simulate the cross-linguistic pattern of OI errors in both declaratives and Wh- questions (see Freudenthal et al., 2015, for a more detailed description of the model and the relevant simulations).

2.2 Running MOSAIC models

MOSAIC is trained by feeding an input corpus through the model multiple times. 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 some utterance-initial words and phrases, 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 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 on the basis of their MLU in words.

For the current simulations, MOSAIC was trained 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 as Freudenthal et al. (2010) used in their comparison of MOSAIC and the VLM. As in Freudenthal et al. (2010), we used versions of the English input corpora that were coded for the occurrence of verbs in 3sg contexts (e.g., *That goes-3SG there; She can go-3SG home; He is going-3SG out*). This feature allows for the identification of verbs that are learned from/produced in 3sg contexts even when no subject is present, and thus for a meaningful comparison of OI error rates in English and in the other languages, where OI errors can be readily identified even when the subject is absent.

2.3 The Novel Defaulting Mechanism

Defaulting was implemented in the model by identifying verb forms that made up more than a criterial proportion (e.g., .65) of the relevant instances of that verb in a large corpus of child-directed speech in each language, and then substituting these high-frequency forms for lower-frequency forms of the same verb in MOSAIC'S output. The setting of the defaulting threshold is inevitably somewhat arbitrary. In the simulations of children's speech at MLU=2, we explore the use of values of .60, .65 and .70. These values were chosen in order 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 MLU=3 and MLU=4, we use values of .85 and .95 for the TD models and .65 and .75 for the DLD models. These values were chosen to allow us to distinguish clearly between the TD and DLD models while at the same time increasing the thresholds used in both sets of models as a function of increasing MLU. Verb counts were collected from both declarative and interrogative input utterances. However, since MOSAIC is based on the assumption that children represent

progressively longer utterance-final strings, the defaulting counts used at different MLUs were based not on corpus-wide statistics, but on utterance-final strings matched to the model's MLU (though corpus-wide statistics were also computed for the purposes of comparison). Thus, defaulting counts for models at MLU=3 were based on utterance-final strings of up to 3 words and defaulting counts at MLU=4 were based on utterance-final strings of up to 4 words. In order to maximise the reliability of these counts, the corpora used were larger than the child-specific corpora used in the actual simulations. These corpora 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 8 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). All of these corpora are available in the CHILDES database (MacWhinney, 2000).

2.4 Defaulting Counts

Since defaulting is assumed to reflect competition between finite forms of the verb, defaulting counts were restricted 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, infinitives were also included in the counts when they occurred in a finite utterance (e.g., *He can go there*, *Does he like that?*) and the finite modal or auxiliary verb form 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, finite utterances were identified by searching the input for subject pronouns and a relevant verb form in an appropriate position. For Spanish,

which allows null subjects, the Mor (morphology) tier of the transcript was used. 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, present tense verbs in simple-finite contexts were marked as tensed (e.g., *He goes-tensed to school*, *They go-tensed home*), while forms in imperative contexts were left unmarked (e.g., *Go home*). This made it possible to distinguish the two forms of *go* when analysing two-word utterance-final strings – *go-tensed home* contributed to the counts for *go*, while *go home* was ignored. Infinitives that occurred in a compound-finite context (e.g., *He can go there*, *Does he go home?*) were marked as modal, while the finite modal or auxiliary was marked 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 modal or auxiliary was not part of the 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. This procedure is designed to simulate the child’s increasing sensitivity to the fact that, in compound-finite contexts, tense is marked on the modal or 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. Pronouns are not included for Spanish as Spanish is a pro-drop language. It can be seen from Table 1 that the English present tense paradigm comprises 2 forms, one of which matches the infinitive, the Dutch paradigm comprises 3 forms, one of which matches the infinitive, the German paradigm comprises 4 forms, one of which matches the infinitive, and the Spanish paradigm comprises 6 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 will default to different forms. For example, English verbs that tend to occur in 3sg contexts (e.g., *fits*) may default to the 3sg form.

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

Infinitive	Run	Rennen	Rennen	Correr
1 st singular	I run	Ik ren	Ich renne	Corro
2 nd singular	You run	Jij rent ²	Du rennst	Corres
3 rd singular	She runs	Zij rent	Sie rennt	Corre
1 st plural	We run	Wij rennen	Wir rennen	Corremos
2 nd plural	You run	Jullie rennen	Ihr rennt	Corréis
3 rd plural	They run	Zij rennen	Sie rennen	Corren

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

² In Dutch (but not German), the 2nd person singular suffix (-t) is omitted in questions and the resultant form is a bare stem, which is homophonous with the 1st person singular form and therefore boosts the frequency of this form in the input.

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 will result in an infinitive that precedes its complement and defaulting from an infinitive to a finite form will result in a finite form that follows its complement.

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

	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)

2.5 Defaulting in MOSAIC's output

Defaulting counts were applied 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 non-default 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*.

Changes were made deterministically rather than probabilistically. Thus, changes were always made when a default had been identified, and never made when no default had been identified. The only exception to this rule was for instances where an infinitive verb form occurred in an utterance with a tensed modal or auxiliary (e.g., *can fit there*). These utterances were left unchanged even if *fits* had been identified as the default form, because they already contain 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), it was assumed that, as utterance length increases, the child becomes increasingly sensitive to the fact that, in compound-finite contexts, tense is marked on the modal or auxiliary rather than on the lexical verb and hence does not substitute tensed verb forms for untensed verb forms in compound finite constructions. Note that this mechanism prevents the model from producing errors such as *kann rent* and *can runs* but still allows 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 modal is absent (e.g., *koffie drinken* → **koffie drinkt*).

3 Simulations and Analyses

3.1 Preview

The present paper reports three sets of simulations and analyses. The first set of simulations (Study 1) focuses on the extent to which adding a defaulting mechanism to MOSAIC improves the model's ability to simulate differences in the rate of OI errors in English, Dutch, German, and Spanish at MLU=2. The second set of analyses (Study 2) focuses on how the novel defaulting mechanism interacts 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. The third set of simulations (Study 3) focuses on whether it is possible to capture the cross-linguistic 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.

3.2 Study 1. Simulating cross-linguistic variation in the rate of OI errors at MLU=2

In this set of simulations, we investigated the extent to which adding a defaulting mechanism to MOSAIC improved the model's ability to simulate the rate of OI errors in English, Dutch, German and Spanish at MLU=2. This was done by comparing the output of models in the absence of defaulting with the output of models after defaulting had been applied with the defaulting threshold set to .60, .65 and .70 in each of the four languages. Output was analysed in the same way as in Freudenthal et al. (2010) by distinguishing between utterances that contained only a non-finite 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 and *runs-3SG*, *can run-3SG is running-3SG* in English). The dependent variable (proportion of OI errors) was the number of utterances in the first category divided by the sum of the utterances in the first and second category³.

3.2.1 Rates of OI errors in MOSAIC in the absence of defaulting

Table 3 shows the rate of OI 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 in Freudenthal et al., 2010). The rates for the models are similar to those reported in Freudenthal et al. (2010), and show that, although MOSAIC provides a reasonably good fit to the child data at MLU=2 ($R^2 = .736$, $F(1, 4) = 11.16$, $p = .029$), it substantially underestimates the proportion of OI errors in early child English (by 30% for

³ A more detailed description of the coding scheme can be found in Appendix B in the materials section.

Anne and 38% for Becky). These results replicate those of Freudenthal et al. (2010) and show that, while MOSAIC's edge-based learning mechanism is sufficient to capture differences in the rate of OI errors across Dutch, German and Spanish, it cannot capture the very high level of OI errors in early child English.

Table 3: Proportion of OI errors in MOSAIC's output at 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	Proportion OI errors Child	Proportion OI errors Model	No. 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	1236
Juan	2.01	.20	.12	824

3.2.2 Rates of OI errors in MOSAIC with defaulting on the basis of utterance-final statistics

Table 4 shows the rate of OI errors in MOSAIC's output after defaulting at thresholds of .60, .65, and .70 on the basis of utterance-final words and two-word strings. It can be seen from these data that defaulting on the basis of utterance-final words and two-word strings results in a much better fit to the child data than was obtained using the previous version of the model ($R^2 = .955$ for the model with a defaulting threshold of .65, compared to $R^2 = .736$ for the original model – R^2 Change = .219, $F(1, 3) = 14.47$, $p = .032$), with differences in the defaulting threshold having little effect on the overall pattern of results. This improvement in

fit is mainly due to a substantial increase in the proportion of OI errors in English (of 34% for Anne’s model and 26% for Becky’s model). However, it also reflects a smaller increase in the proportion of OI errors in Dutch (of 5% for Matthijs’s model and 7% for Peter’s model), with the proportion of OI errors in German and Spanish being largely unaffected. These results show that combining MOSAIC’s utterance-final bias with a mechanism that defaults to the most frequent form of the verb provides a better explanation of the cross-linguistic data.

Table 4: Proportion of OI errors in MOSAIC’s output at 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. (Proportion of affected utterances in parentheses.)

Child	MLU	Proportion OI errors Child	Proportion OI errors Model Threshold=.60	Proportion OI errors Model Threshold=.65	Proportion 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)

3.2.3 Rates of OI errors in MOSAIC with defaulting on the basis of corpus-wide statistics

Table 5 shows the rate of OI errors in MOSAIC’s output after defaulting at thresholds of .60, .65, and .70 on the basis of utterance-final strings of up to 10 words in length (effectively on

the basis of a corpus-wide analysis). These data are interesting because they suggest that defaulting on the basis of corpus-wide statistics results in a poorer fit to the child language data than defaulting on the basis of utterance-final statistics. This is partly because it results in a much less pronounced increase in the proportion of OI errors in English (of 11% for both Anne and Becky's models compared to 34% and 26%, respectively, for the previous models). However, it is also because it results in a decrease in the proportion of OI 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 is not particularly surprising since, in both languages, although the infinitive is the most common form of the verb in utterance-final position, it is not the most common form of the verb in the input as a whole. However, it does underline the need to link defaulting to the model's utterance-final bias in learning in order to explain the cross-linguistic data.

In summary, the simulations presented above show that adding a defaulting mechanism to MOSAIC allows the model to simulate the very high rate of OI errors in early child English without affecting the model's previously good fit to the data on Dutch, German and Spanish. However, they also show that this is only the case when the defaulting counts are based on utterance-final phrases matched to the model's MLU. They therefore underline the important role played by MOSAIC's utterance-final bias in explaining the developmental data.

Table 5: Proportion of OI errors in MOSAIC's output at 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. (Proportion of affected utterances in parentheses).

Child	MLU	Proportion OIs Child	Proportion OIs Model Threshold=.60	Proportion OIs Model Threshold=.65	Proportion OIs 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)

3.3 Study 2. Defaulting as a function of the statistics of child-directed speech in the four languages

In this set of analyses, we investigated how the defaulting mechanism interacted with the frequency statistics of child-directed speech in the four languages. This was done by setting the defaulting parameter to .65 and exploring the pattern of defaulting and the proportion of affected verbs for defaulting counts based on utterance-final strings of different lengths in the child-directed speech corpora.

Tables 6 to 9 show the results of these analyses for each of the four languages. Results are expressed as the proportion of verbs that would be subject to defaulting, based on a threshold of .65. Results are shown for utterance-final words and utterance-final strings of 2, 3, 5, and 10 words. Complete utterances are included in string sets that exceed 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.

Results for the English input analysis are presented in Table 6. It is clear from these data that the vast majority of English verbs would default to the bare form (i.e., occur as a bare form in over 65% of tensed contexts). Fewer verbs would default to the bare form in longer strings. This is due to the fact that untensed forms in compound structures contribute to the counts for short, but not for longer strings, which are more likely to include both a tensed modal or auxiliary and an untensed lexical verb (e.g., *That might-tensed go-modal there*).

Table 6: Proportion of verbs that would default to a particular form of the verb in English at different maximum string lengths. Complete utterances are included in string sets that exceed their length.

String Length	Bare Form	3 rd Sg.	No default	N
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

Nevertheless, even in the 10-word string analysis, more than 80% of verbs would default to the bare form. This reflects 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 has such a profound effect on the rate of OI errors in English. It also suggests that allowing the model to default at high MLUs (on the basis of statistics from longer utterance-final strings) may be an effective way of simulating the

higher rate of OI errors in English-speaking children with DLD relative to MLU-matched controls. This is because defaulting on the basis of statistics from longer utterance-final strings will increase the rate of OI errors in the model's output without affecting the model's MLU.

Results for the Dutch and German analyses are presented in Tables 7 and 8. It is clear from these data that fewer verbs would default to the infinitive in Dutch and German than would default 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 changes as string length increases. The infinitive (stem+en) form is the most common default for utterance-final words and two- and three-word strings, but for longer strings the 1st and 2nd singular (stem) in Dutch and the 3rd singular (stem+t) in German are the most common defaults.

This pattern reflects the SOV/V2 nature of Dutch and German, where non-finite forms (including the infinitive) take utterance-final position, whereas finite forms take second position and precede their complements. Non-finite forms are therefore more likely to occur in short utterance-final strings, while finite forms are more likely to occur in longer strings.

Table 7: Proportion of verbs that would default to a particular form of the verb in Dutch at different maximum string lengths. Complete utterances are included in string sets that exceed their length.

String Length	Infinitive (Stem+en)	1 st /2 nd SG (Stem)	2 nd /3 rd SG (Stem+t)	No default	N
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

Table 8: Proportion of verbs that would default to a particular form of the verb in German at different maximum string lengths. Complete utterances are included in string sets that exceed their length.

String Length	Infinitive (Stem+en)	1st SG (Stem+e)	2nd SG (Stem+st)	3rd SG (Stem+t)	No default	N
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

The fact that fewer Dutch and German verbs show a strong preference for the infinitive explains why the model's defaulting mechanism has less effect on the rate of OI errors in Dutch and German than it does in English; and the fact that the pattern of preference changes

as a function of string length explains why it is 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 suggest that allowing the model to default at high MLUs (on the basis of 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 OI errors at high MLUs.

Results for the Spanish input analysis are presented in Table 9. Plural forms are not included in the table because there were no verbs that would default to a plural verb form at any string length. Compared to Dutch and German, the pattern in Spanish is relatively stable. Most verbs would not be subject to defaulting, regardless of string length. However, 15 to 25% would default to the 3sg form.

This pattern of defaulting is likely to result in the replacement of low frequency finite forms with high frequency 3sg forms rather than the replacement of finite forms with infinitives, and explains why the model's defaulting mechanism has so little effect on the rate of OI errors in Spanish. It is also consistent with the pattern of verb-marking error 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 3sg forms.

Table 9: Proportion of verbs that would default to a particular form of the verb in Spanish at different maximum string lengths. Complete utterances are included in string sets that exceed their length.

String Length	Infinitive	1 st SG	2 nd SG.	3 rd SG	No default	N
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

Finally, it suggests that allowing the model to default at high MLUs (on the basis of statistics from longer utterance-final strings) would simply prolong the period during which agreement errors were made, which is broadly consistent with the data on verb-marking error in Spanish-speaking children with DLD, who tend to show slightly higher rates of agreement error relative to age-matched, though not necessarily MLU-matched controls (Bedore & Leonard, 2001; 2005).

In summary, the input analyses presented above reveal that English verbs show an overwhelming preference for the bare form, which is consistent across different string lengths. Fewer verbs show a strong preference in Dutch and German, and the preferred form changes as a function of string length. In short strings there tends to be a preference for the infinitive, which occurs in utterance-final position; in longer strings there tends to be a preference for finite forms, which occur in V2. Even fewer verbs show a strong preference in Spanish, but where they do, this tends to be a preference for the 3sg form. These input analyses therefore explain why defaulting has a large effect on the rate of OI errors in

English, a smaller effect in Dutch and German and virtually no effect in Spanish. They also suggest that defaulting at higher MLUs will tend to increase the rate of OI errors in English, but not in Dutch, German or Spanish, where it is likely to result in defaulting to the highest frequency finite form and hence to agreement and positioning rather than OI errors.

3.4 Study 3. Simulating the cross-linguistic pattern of verb-marking error in children with DLD

In this set of simulations, we investigated the model's ability to capture the cross-linguistic pattern of verb-marking error in TD children and children with DLD. This was done by applying different defaulting thresholds to the output from each of the children's models at MLU=3 (on the basis of utterance-final strings of up to 3 words) and MLU=4 (on the basis of utterance-final strings of up to 4 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 will result in higher levels of defaulting error, these values were chosen to result in higher levels of defaulting in the DLD than the TD models and decreasing levels of defaulting as a function of MLU. Rates of OI errors were calculated in the same way as in the first set of analyses. Rates of agreement error were calculated 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. Rates of verb positioning errors in Dutch and German were calculated 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 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. Rates of OI errors (Panel a) and Agreement errors (Panel b) for each TD model and the equivalent model with a lower defaulting threshold (DLD)

Figure 1 shows the rates of OI errors (panel a) and agreement errors (panel b) in each TD model and the equivalent model with a lower defaulting threshold (DLD). Differences in the rates of OI and agreement errors between each pair of models were analysed using Chi-square tests, the details of which are provided in Table 10.

Table 10: Rates of OI and Agreement Errors in the English (Anne and Becky), Dutch (Matthijs and Peter), German (Leo) and Spanish (Juan) models and the equivalent models with a lower defaulting threshold (DLD)

Model	OI errors	Correct	%Error	Agreement errors	Correct	%Error
Anne MLU=3	822	405	67.0	0	394	0
Anne-DLD MLU=3	894	231	73.0	0	319	0
	$\chi^2 = 45.66, p < .0001$					
Anne MLU=4	1704	1846	48.0	0	1471	0
Anne-DLD MLU=4	2092	1453	59.0	0	1115	0
	$\chi^2 = 86.03, p < .0001$					
Becky MLU=3	401	303	57.0	1	306	0.3
Becky-DLD MLU=3	444	260	63.1	1	350	0.3
	$\chi^2 = 5.22, p = .0223$					
Becky MLU=4	557	835	40.0	1	1328	0.1
Becky-DLD MLU=4	751	640	54.0	4	1148	0.3
	$\chi^2 = 53.99, p < .0001$					
Mathijs MLU=3	1415	1112	56.0	22	805	2.7
Mathijs-DLD MLU=3	1438	1085	57.0	69	738	8.6

	$\chi^2 = 0.49, p = .493$			$\chi^2 = 25.83, p < .0001$		
Mathijs MLU=4	1568	3184	33.0	11	2157	0.5
Mathijs-DLD MLU=4	1568	3182	33.0	97	2062	4.5
	$\chi^2 = 0.00, p = 1.000$			$\chi^2 = 68.97, p < .0001$		
Peter MLU=3	1578	1779	47.0	28	1286	2.1
Peter-DLD MLU=3	1568	1769	47.0	123	1168	9.5
	$\chi^2 = 0.00, p = 1.000$			$\chi^2 = 63.90, p < .0001$		
Peter MLU=4	1293	4327	23.0	24	2977	0.8
Peter-DLD MLU=4	1349	4273	24.0	116	2839	3.9
	$\chi^2 = 1.47, p = .225$			$\chi^2 = 62.03, p < .0001$		
Leo MLU=3	2892	3535	45.0	83	2815	2.9
Leo-DLD MLU=3	2890	3532	45.0	180	2675	6.3
	$\chi^2 = 0.00, p = 1.000$			$\chi^2 = 38.24, p < .0001$		
Leo MLU=4	3484	7754	31.0	36	6063	0.6
Leo-DLD MLU=4	3379	7885	30.0	293	5896	4.7
	$\chi^2 = 2.63, p = .102$			$\chi^2 = 200.85, p < .0001$		
Juan MLU=3	841	6169	12.0	51	4751	1.1
Juan-DLD MLU=3	842	6172	12.0	254	4583	5.3
	$\chi^2 = 0.00, p = 1.000$			$\chi^2 = 136.65, p < .0001$		
Juan MLU=4	952	9625	9.0	31	6922	0.4
Juan-DLD MLU=4	953	9635	9.0	230	6750	3.3
	$\chi^2 = 0.00, p = 1.000$			$\chi^2 = 152.29, p < .0001$		

It is clear from Figure 1 that reducing the defaulting threshold at higher MLUs does have an effect on the rate of OI errors in the English models, resulting in increases of 6% at MLU=3

and 11 and 14% at MLU=4, all $ps < .025$ by Chi-square). However, it is also clear that it has little or no effect on the rate of OI errors in the Dutch, German and Spanish models (all $ps > .10$). It therefore allows the model to simulate the increased rate of OI errors relative to MLU-matched controls seen in English-speaking children with DLD, but not in Dutch-, German- and Spanish-speaking children. In contrast, reducing the defaulting threshold at higher MLUs in the Dutch, German and Spanish models results in increased rates of agreement error. These increases can be seen in all 3 languages at both MLU points (all $ps < .0001$). However, they result in relatively low overall error rates (never greater than 10%). They are therefore consistent with the cross-linguistic literature on DLD, which reports elevated, but still relatively low, rates of agreement error in Dutch-, German- and Spanish-speaking children.

Finally, as 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. The rates at which such errors occur in the Dutch and German models are reported in Table 11. It can be seen from these data, that although positioning errors are more common in the DLD than the TD models at both MLU points (all $ps < .0002$ by Chi-square), they are nevertheless relatively rare (ranging from 0 to 2.1% in the TD models and 2.0 to 6.4% in the DLD models). These results are consistent with the literature on child Dutch and German, where positioning errors are rare in TD children, particularly at high MLUs, but occur at elevated though still relatively low rates in children with DLD. They thus provide further support for the idea that a Dual-Factor Model in which defaulting occurs at different rates in impaired and unimpaired children provides a plausible account of the cross-linguistic pattern of verb-marking error in TD children and children with DLD.

Table 11: Rates of Positioning Errors in the Dutch (Matthijs and Peter) and German (Leo) models and the equivalent models with a lower defaulting threshold (DLD)

Model	Finites in Final Position	Finites in V2	%Error	Infinitives in V2	Infinitives in Final Position	%Error
Mathijs MLU=3	10	817	1.2	15	1396	0.1
Mathijs-DLD MLU=3	46	761	5.7	46	1381	3.2
	$\chi^2 = 23.55, p < .0001$			$\chi^2 = 14.73, p = .00012$		
Mathijs MLU=4	4	2164	0.2	0	1571	0
Mathijs-DLD MLU=4	54	2105	2.5	32	1550	2.0
	$\chi^2 = 42.17, p < .0001$			$\chi^2 = 30.12, p < .0001$		
Peter MLU=3	8	1306	0.6	33	1536	2.1
Peter-DLD MLU=3	82	1209	6.4	74	1497	4.7
	$\chi^2 = 62.68, p < .0001$			$\chi^2 = 15.43, p < .0001$		
Peter MLU=4	18	2983	0.6	0	1304	0
Peter-DLD MLU=4	58	2897	2.0	76	1268	5.7
	$\chi^2 = 20.89, p < .0001$			$\chi^2 = 73.90, p < .0001$		
Leo MLU=3	17	2881	0.6	17	2871	0.6
Leo-DLD MLU=3	79	2776	2.8	72	2850	2.5
	$\chi^2 = 40.35, p < .0001$			$\chi^2 = 32.64, p < .0001$		
Leo MLU=4	18	6081	0.3	3	3463	0.1
Leo-DLD MLU=4	130	6059	2.1	67	3342	2.0
	$\chi^2 = 82.63, p < .0001$			$\chi^2 = 58.35, p < .0001$		

In summary, modelling the verb-marking deficit in DLD in terms of an increased tendency to default to the most common form of the verb captures both the tendency of English-speaking children with DLD to produce OI 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 suggests that a Dual-Factor model of verb-marking error has the potential to explain both the cross-linguistic pattern of verb-marking error in TD children and the cross-linguistic pattern of verb-marking deficit in children with DLD.

4. Discussion

The aim of the present study was to investigate whether a Dual Factor 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 cross-linguistic data on TD children and a means of simulating the cross-linguistic pattern of verb-marking deficit in 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 cross-linguistic pattern of OI errors in TD children at MLU=2. Our results show that the addition of a defaulting mechanism allows MOSAIC to simulate the very high rate of OI 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 OI errors in English reflect a process of defaulting to the most frequent form of the verb (Räsänen et al., 2014; Kueser et al., 2018), and suggest that the very high rate of OI 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.

At this point, it might be tempting to ask whether defaulting could provide a viable single-factor model of the cross-linguistic patterning of OI errors. However, there are at least two

reasons why this cannot be the case. The first is that some additional mechanism (such as MOSAIC's utterance-final bias in learning) is necessary to explain the cross-linguistic pattern of OI errors in languages other than English. Thus, since the infinitive is rarely the most frequent form of the verb in Dutch and German, defaulting on its own could not explain why Dutch- and German-speaking children initially produce OI errors at such high rates, nor why when they do produce such errors, they tend to place the infinitive in correct utterance-final position. The second is that, even in the current version of MOSAIC, the addition of a defaulting mechanism only results in a better explanation of the data when the defaulting counts are based on utterance-final phrases matched to the model's MLU. The implication is that, although some kind of defaulting mechanism is necessary to explain the very high rates of OI error in early child English, the kind of utterance-final learning bias instantiated in MOSAIC is also crucial to our understanding of the relationship between the rates at which children make OI errors in different languages and the distributional properties of the language to which they are exposed.

In a second set of analyses, we investigated how the novel defaulting mechanism interacted with the frequency statistics of child-directed speech in the 4 languages across utterance-final strings of different lengths. The results of these analyses show that defaulting is likely to result in bare stem errors in English and 3sg errors in Spanish regardless of string length. However, they also show 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 on the basis of short utterance-final strings is likely to result in OI errors and infinitives in V2, whereas defaulting on the basis of longer utterance-final strings is likely to result in agreement errors and finite forms in utterance-final position. These findings show that defaulting can explain why English-speaking children tend to make bare stem errors in their speech, whereas Spanish children tend to make 3sg errors.

They also show why it is necessary to allow defaulting to interact with MOSAIC's utterance-final bias in learning in order to explain the Dutch and German data at MLU=2. The reason is that defaulting on the basis of corpus-wide statistics would reduce the rate of OI errors in the model's output by reducing the number of infinitives and increasing the number of finite forms. Finally, they suggest that defaulting on the basis of the statistics of longer utterance-final strings will tend 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 cross-linguistic pattern of differences in the rate of OI, agreement and verb-positioning errors in TD children and 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 OI 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 significantly higher in the DLD than the TD models, the rates of agreement and positioning errors are never unrealistically high (i.e., never greater than 10%). Note that 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 reported in detailed analyses of the speech of children learning

more highly inflected languages (e.g., Aguado-Orea & Pine, 2015; Engelmann et al. 2019; Räsänen et al., 2016; Rubino & Pine, 1998).

Overall, these findings suggest that a Dual-Factor Model in which defaulting occurs at different rates in impaired and unimpaired children provides a plausible account of the cross-linguistic pattern of verb-marking error in TD children and the cross-linguistic pattern of verb-marking deficit in children with DLD. However, since different levels of defaulting are implemented in the current model by directly manipulating the defaulting parameter, this conclusion still leaves unanswered the question of what underlying mechanism is responsible for the different levels of defaulting seen in TD children and children with DLD. One possibility that maps more or less directly on to the way defaulting is implemented 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, Klein-Packard, & Tomblin (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 the ability to learn low frequency forms and morphological patterns that leaves the child with DLD more susceptible to competition from high frequency forms of the verb (see Harmon, Barak, Shafto, Edwards, & Feldman (2021) for an account of deficits in past tense marking along these lines). And a third possibility is that greater defaulting reflects a deficit in the 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 longer than TD children (see Leonard, Fey, Deevy, & Bredin-Oja (2015) for a more detailed description of this Competing Sources of Input account, and Freudenthal, Ramscar, Leonard, & Pine (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 the present study — and, given the multi-faceted nature of DLD, it is possible that all of them may have some role to play. However, what this study does show is that a Dual-Factor model that incorporates the kind of defaulting mechanism implemented here can explain both the cross-linguistic pattern of OI errors in TD children and the cross-linguistic pattern of verb-marking deficit in children with DLD. This model has several advantages over previous models of verb-marking error. First, it can explain the very high rate of OI errors in early child English. Second, it can explain why children learning languages other than English tend to make both OI and agreement errors in their speech. Third, it can explain why English-speaking children with DLD produce OI errors at higher rates than language-matched controls, whereas children learning other languages tend to make more agreement and positioning errors. Finally, it suggests a number of avenues for future research which have the potential to further increase our understanding of the factors that underlie the verb-marking deficit in children with DLD.

References

Aguado-Orea, J. & Pine, J. M. (2015). Comparing different models of the development of verb inflection in early child Spanish. *PloS One*, 10(3), e0119613.

- Bedore, L. M. & Leonard, L. B. (2001). Grammatical morphology deficits in Spanish-speaking children with specific language impairment. *Journal of Speech, Language, and Hearing Research*, 44, 905-924.
- Bedore, L. M. & Leonard, L. B. (2005). Verb inflections and noun phrase morphology in the spontaneous speech of Spanish-speaking children with specific language impairment. *Applied Psycholinguistics*, 26, 195-225.
- Behrens, H. (2006). The input-output relationship in first language acquisition. *Language and Cognitive Processes*, 21, 2–24.
- Bloom, P. (1990). Subjectless sentences in child language. *Linguistic Inquiry*, 21, 491-504.
- Bol, G. W. (1995). Implicational scaling in child language acquisition: The order of production of Dutch verb constructions, In M. Verrips & F. Wijnen (Eds.), Papers from *The Dutch-German Colloquium on Language Acquisition, Amsterdam Series in Child Language Development*, 3, Amsterdam: Institute for General Linguistics.
- Bol, G. W. (1996). Optional subjects in Dutch child language, In C. Koster & F. Wijnen (Eds.), *Proceedings of the Groningen Assembly on Language Acquisition*, 125–135. Groningen, The Netherlands: Centre for Language and Cognition.
- Brown, R. (1973). *A first language: The early stages*. Cambridge, MA: Harvard University Press.
- Clahsen, H., Bartke, S., & Göllner, S. (1997). Formal features in impaired grammars: A comparison of English and German SLI children. *Journal of Neurolinguistics*, 10, 151-171.
- de Jong, J. (1999). Specific language impairment in Dutch: Inflectional morphology and argument structure. *Groningen Dissertations in Linguistics*.
- Engelmann, F., Kolak, J., Granlund, S., Szreder, M., Ambridge, B., Pine, J., Theakston, A. & Lieven, E. (2019). How the input shapes the acquisition of verb morphology: Elicited

- production and computational modelling in two highly inflected languages. *Cognitive Psychology*, 110, 30-69.
- Freudenthal, D., Pine, J. M. & Gobet, F. (2006). Modelling the development of children's use of optional infinitives in Dutch and English using MOSAIC. *Cognitive Science*, 30, 277-310.
- Freudenthal, D., Pine, J. M. & Gobet, F. (2009). Simulating the referential properties of Dutch, German and English root infinitives. *Language Learning and Development*, 5, 1-29.
- Freudenthal, D., Pine, J. M. & Gobet, F. (2010). Explaining quantitative variation in the rate of Optional Infinitive errors across languages: A comparison of MOSAIC and the Variational Learning Model. *Journal of Child Language*, 36, 643-669.
- Freudenthal, D., Pine, J. M., Aguado-Orea, J. & Gobet, F. (2007). Modelling the developmental patterning of finiteness marking in English, Dutch, German and Spanish using MOSAIC. *Cognitive Science*, 31, 311-341.
- Freudenthal, D., Pine, J. M., Jones, G. & Gobet, F. R. (2015). Simulating the cross-linguistic pattern of Optional Infinitive errors in children's declaratives and Wh- questions. *Cognition*, 143, 61-76.
- Freudenthal, D., Ramscar, M., Leonard, L. B. & Pine, J. M. (2021). Simulating the acquisition of verb inflection in typically developing children and children with Developmental Language Disorder in English and Spanish. *Cognitive Science*, 45(3), e12945.
- Grinstead, J., De la Mora, J., Vega-Mendoza, M., & Flores, B. (2009). An elicited production test of the optional infinitive stage in child Spanish. In J. Crawford, K. Otaki, & M. Takahashi (Eds.), *Proceedings of the 3rd Conference of Generative Approaches to Language Acquisition North America* (pp. 36-45). Somerville, MA: Cascadilla Press.

- Hamann, C., Penner, Z. & Lindner, K. (1998). German impaired grammar: The clause structure revisited. *Language Acquisition*, 7, 193-245.
- Harmon, Z., Barak, L., Shafto, P., Edwards, J. & Feldman, N. H. (2021). Making heads or tails of it: A competition-compensation account of morphological deficits in language impairment. In *Proceedings of the 43rd Annual Conference of the Cognitive Science Society*. Vienna, Austria: Cognitive Science Society.
- Kueser, J. B., Leonard, L. B., & Deevy, P. (2018). Third person singular -s in typical development and specific language impairment: Input and neighbourhood density. *Clinical Linguistics & Phonetics*. 32(3), 232-248.
- Legate, J. A. & Yang, C. (2007). Morphosyntactic learning and the development of tense. *Language Acquisition*, 14(3), 315-344.
- Leonard, L. B. (2014). *Children with specific language impairment* (2nd Edition). Cambridge, MA: MIT Press.
- Leonard, L. B., Fey, M., Deevy, P., & Bredin-Oja, S. (2015). Input sources of third person singular –s inconsistency in children with and without specific language impairment. *Journal of Child Language*, 42, 786-820.
- List, C. & Pine, J. M. (in press). Testing the Extended Optional Infinitive Hypothesis in a German child with DLD. In P. Jordens & D. Bittner (Eds.), *Driving forces in language development*.
- MacWhinney, B. (2000). *The CHILDES project: Tools for analyzing talk* (3rd Edition). Mahwah, NJ: Erlbaum.
- McMurray, B., Klein-Packard, J. & Tomblin, J. B. (2019). A real-time mechanism underlying lexical deficits in developmental language disorder: Between-word inhibition. *Cognition*, 191, 104000.

- Pine, J. M., Freudenthal, D. & Gobet, F. (2020). Understanding the cross-linguistic pattern of verb-marking error in typically developing children and children with Developmental Language Disorder: Why the input matters. In C. F. Rowland, B. Ambridge, A. L. Theakston & K. E. Twomey (Eds.), *Current perspectives on child language acquisition: How children use their environment to learn*. Amsterdam: John Benjamins.
- Räsänen, S. H. M., Ambridge, B. & Pine, J. M. (2014). Infinitives or bare stems? Are English-speaking children defaulting to the highest frequency form? *Journal of Child Language*, 41, 756-779.
- Räsänen, S. H. M., Ambridge, B. & Pine, J. M. (2016). Comparing generativist and constructivist accounts of the acquisition of inflectional morphology: An elicited production study of Finnish. *Cognitive Science*, 40(7), 1704-1738.
- Rice, M. L., Noll, K. R., & Grimm, H. (1997). An Extended Optional Infinitive Stage in German-Speaking Children with Specific Language Impairment. *Language Acquisition*, 6, 255-295.
- Rice, M.L., Wexler, K., & Cleave, P.L. (1995). Specific Language Impairment as a period of extended optional infinitive. *Journal of Speech and Hearing Research*, 38, 850-863.
- Rice, M., Wexler, K., & Hershberger, S. (1998). Tense over time: the longitudinal course of tense acquisition in children with specific language impairment. *Journal of Speech, Language, and Hearing Research*, 41, 1412-1431.
- Roberts, S. S. & Leonard, L. B. (1997). Grammatical deficits in German and English: a crosslinguistic study of children with specific language impairment. *First Language*, 17, 131-150.
- Rothweiler, M., Chilla S., & Clahsen, H. (2012). Subject-verb agreement in Specific Language Impairment: A study of monolingual and bilingual German-speaking children. *Bilingualism: Language and Cognition*, 15(1), 39-57.

- Rubino, R. & Pine, J. M. (1998). Subject-verb agreement in Brazilian Portuguese: what overall error-rates hide. *Journal of Child Language*, 25, 35-59.
- Salustri, M., & Hyams, N. (2003). Is there an analogue to the RI stage in the null subject languages? *Proceedings of the Annual Boston University Conference on Language Development*, 27, 692–703.
- Theakston, A. L., Lieven, E. V. M., Pine, J. M. & Rowland, C. F. (2001). The role of performance limitations in the acquisition of verb-argument structure: An alternative account. *Journal of Child Language*, 28, 127-152.
- Valian, V. (1991). Syntactic subjects in the early speech of American and Italian children. *Cognition*, 40, 21-81.
- Wexler, K. (1994). Optional infinitives, head movement and the economy of derivation in child grammar. In N. Hornstein & D. Lightfoot (Eds.), *Verb Movement* (pp. 305-350). Cambridge: Cambridge University Press.
- Wexler, K., Schaeffer, J. & Bol, G. (2004). Verbal syntax and morphology in typically developing Dutch children and children with SLI: how developmental data can play an important role in morphological theory. *Syntax*, 7(2), 148-198.