Typicality biases in interpreting unmarked sentences: an artificial language learning experiment on differential argument marking

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Abstract

Many languages exhibit Differential Argument Marking (DAM), where nouns are marked for their grammatical role only in certain contexts. DAM is subdivided into Differential Object Marking (DOM) and Differential Subject Marking (DSM), both of which are conditioned by factors such as animacy across languages and hypothesized to arise via ambiguity avoidance and tendencies to mark atypical situations. While previous studies have primarily focused on production, this study employs artificial language learning to investigate comprehension in both DOM and DSM, examining whether learners rely on typicality biases for grammatical role assignment in unmarked sentences, and whether the type of marking learned affects their interpretation. Results indicate a strong givenness effect and a smaller animacy effect, with no significant differences between DOM and DSM conditions. These findings suggest that typicality biases play a key role in shaping DAM systems and that their emergence is best understood as a communicative phenomenon.

Keywords: differential argument marking; artificial language learning; information structure; word order; typicality

Introduction

Languages are diverse (Evans & Levinson, 2009), yet many of them exhibit common structural features. One of the primary goals of linguistics is to elucidate how these structural similarities arise, a question increasingly explored through artificial language learning experiments that investigate the connection between common typological patterns and cognitive biases (Culbertson, 2012; Culbertson, Franck, Braquet, Navarro, & Arnon, 2020; Fedzechkina, Jaeger, & Newport, 2012; Fedzechkina, Newport, & Jaeger, 2017; Kam & Newport, 2005; Kurumada & Grimm, 2019; Martin & Peperkamp, 2020; Tal, Smith, Culbertson, Grossman, & Arnon, 2022). In this study, we use an artificial language learning paradigm to explore how cognitive biases may give rise to Differential Argument Marking (DAM), paying special attention to how learners interpret ambiguous sentences during comprehension, with regard to word order, animacy, and information structure.

DAM can generally be split into two categories: differential object marking (DOM: sentences 1a-b) and differential subject marking (DSM: sentences 2a-b). DOM is where only a subset of direct objects receive grammatical marking, while others are left unmarked (Bossong, 1985; Iemmolo, 2010; Moravcsik, 1978; Witzlack-Makarevich & Seržant, 2018). DSM, on the other hand, is where a subset of subjects receives grammatical marking, while others are left unmarked (Aissen, 2003; Woolford, 2009; Silverstein, 1976). Crucially, in these DAM systems, the occurrence of marking is not arbitrary, but is instead impacted by semantic and discourse-related properties, such as animacy, definiteness, and information structure. More specifically, marking in DOM tends to be conditioned by animate, definite, or topical objects, e.g., as in Persian, Spanish, and Burmese (Clair, 2016; Karimi, 1990; Ozerov, 2015; Okell, 1969; Iemmolo, 2020), while marking in DSM tends to be conditioned by inanimate or contrastive subjects, e.g., as in Azhee, Fore, and Burmese (Gerner, 2016; Scott, 1978; Jenny & Tun, 2013).

(1) Spanish: DOM conditioned by animacy (Haspelmath, 2021a)

a. Veo a la mujer.
see.PRS.1SG OBJ the woman
'I see the woman.'

b. Veo la casa.
see.PRS.1SG the house
'I see the house.'

(2) Fore: DSM conditioned by animacy (Scott, 1978)

a. Yagaa-wama wá aegúye
pig-SUBJ man hit
'The pig hits the man.'

b. Yagaa wá aegúye.
pig man hit
'The man hits (or kills) the pig.'

Accordingly, the conditions for DOM and DSM seem to mirror each other: direct objects tend to be more marked when they are atypical (i.e., having properties more typical of a subject), and subjects tend to be more marked when they are atypical (i.e., having properties more typical of an object) (Levshina, 2021; Witzlack-Makarevich & Seržant, 2018). Figure 1 summarizes this in the form of referential scales (Croft, 2003).

definite > indefinite
human > animal > inanimate
first, second person > third person
given information > new information

⟵	⟶
Unmarked subject referent	**Marked subject referent**
Marked object referent	Unmarked object referent

Figure 1: A referential scale showing what is typical/atypical of object and subject referents. Properties to the left are more typical of subjects; properties to the right are more typical of objects.

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Inconsistencies in DAM

Despite cross-linguistic tendencies, DAM systems show inconsistencies (DOM: e.g., Sinnemäki, 2014; DSM: e.g., Woolford, 2009). In some languages, e.g., Balto-Slavic and Finnic (including Estonian), DOM is conditioned by properties of the predicate (e.g., verbal aspect, polarity, and boundedness) (Iemmolo, 2013; de Swart, 2006; Malchukov & de Hoop, 2011). Conversely, DSM is conditioned by agency or TAM in some languages, such as Hindi, which often contradicts the marking of atypical referential properties (e.g., DeLancey, 1981; Coon, 2013). DSM also appears to be less common compared to DOM (Aissen, 2003). While some explanations exist for such disparities (Luraghi, Smit, & Igartua, 2020; Iemmolo, 2013; Dalrymple & Nikolaeva, 2011), it is apparent that predictability alone does not account for all DAM systems and should accordingly be validated via experimental methods for both DOM and DSM.

Cognitive and communicative pressures

Two of the more prominent functional explanations for the emergence of DAM are ambiguity avoidance (Bossong, 1985; Comrie, 1978; Dixon, 1994) and predictability-based marking (Haspelmath, 2019, 2021a, 2021b; Levshina, 2021). Ambiguity avoidance posits that DAM arises to distinguish subjects and objects where they would otherwise be ambiguous (e.g., when both are animate). Predictability-based marking posits that atypical associations between a referent and its grammatical role (e.g., animate objects) are unexpected and thus motivate the development of DAM. While these two functional explanations are commonly framed as competing notions (e.g., Haspelmath, 2019, 2021a; Tal et al., 2022), both accounts are compatible with the communicative efficiency framework (Gibson et al., 2019; Levshina & Moran, 2021; Kanwal, Smith, Culbertson, & Kirby, 2017; Kurumada & Jaeger, 2015; Pate & Goldwater, 2015) and lead to similar predictions—since ambiguity often arises when a role assignment is less predictable.

Experimental research on DAM via artificial language learning has primarily focused on production rather than comprehension. For example, Fedzechkina et al. (2012) show that, after training in a language with flexible word order, animate and inanimate objects, and optional marking (i.e., not conditioned by animacy), participants diverged from the input language by marking animate objects more frequently and inanimate objects less frequently—potentially to reduce ambiguity. One issue with their design, however, is that specific animate characters had fixed roles as either a subject or an object (but not both), which lends itself to an alternative interpretation of the results: the learners were producing redundant marking. This is, in fact, corroborated by the findings of Smith and Culbertson (2020), showing that participants' tendency to over- or undermark animate objects depended on the frequency of marking in the input rather than on ambiguity or the object's animacy, even when the roles of animate characters were not fixed.

Tal et al. (2022) tested the predictability-based marking account with a language learning paradigm modeled after Fedzechkina et al. (2012), with two crucial differences: arguments were always animate and information structure was manipulated by introducing one of the actors before the event. They found that participants were not more likely to use the object marker on atypical given objects; however, information structure had an indirect effect on object marking, in which given objects elicited more OSV word order, which then resulted in increased marking of the object. Interestingly, Fedzechkina et al. (2012) also report word order effects, though differing by type of marking: OSV received more marking (and SOV more unmarked) with DOM, whereas SOV received more marking (and OSV more unmarked) in their DSM condition. They interpret this as a bias to mention disambiguating information as early as possible.

All of these production-oriented studies leave a key question unanswered: How do learners actually interpret (comprehend) ambiguous sentences, and does that interpretation systematically involve typicality (i.e., animacy, information structure) in a way that might motivate the emergence of marking? Communication, after all, involves both speaking and listening, and Smith and Culbertson (2020) have found that ambiguity avoidance only influences object marking production in communicative tasks as opposed to one-sided production tasks. When there is no pressure to communicate, there is not pressure to disambiguate in production, as the speaker can describe an event with no intention of being understood. Listeners, on the other hand, would assume communicative intent (Sperber & Wilson, 1995) and rely on some bias to resolve ambiguous situations consistently. Additionally, these experiments generally focus on a single parameter (i.e.; animacy in Fedzechkina et al., 2012; Smith & Culbertson, 2020; information structure in Tal et al., 2022) and have yet to investigate their interactions. Therefore, empirically verifying these typicality biases and assessing their effects on ambiguous sentence comprehension—across both DOM and DSM systems—is crucial for understanding how DAM arises and for designing future experiments.

The experiment

We employ an artificial language learning paradigm to investigate how listeners interpret ambiguous sentences and whether typicality biases (based on animacy and information structure) influence comprehension. Specifically, we address the following questions: 1) Do participants assign grammatical roles based on typicality (i.e., animacy, information structure) when ambiguity is present (i.e., unfixed word order with no marking)? 2) Does the presence of object marking vs. subject marking in the input affect how ambiguous (unmarked) situations are understood (i.e., word order preferences)?

To investigate these questions, we tested the learning and comprehension of two artificial languages, identical except for their marking systems, one involving DOM and the other DSM. In both languages, we manipulate the animacy and information structure of arguments that are predicted to elicit typicality biases. If typicality plays a role in assigning grammatical roles, then the interpretation of subjects and objects in unmarked sentences should be affected accordingly. In other words, if an actor is given or animate, then participants are expected to be more likely to interpret it as the subject. Conversely, if an actor is new or inanimate, then participants are expected to be more likely to interpret it as the object. Drawing on prior proposals on the role of information structure in the emergence of DOM (Iemmolo, 2010, 2020), we predict that the argument order of unmarked sentences will be largely affected by typicality in terms of information structure (i.e., the given element is assigned the subject role and the new element is assigned the object role) more than animacy. Additionally, if typicality biases apply equally to both DOM and DSM in comprehension, then the type of system learned (DSM vs. DOM) should not affect the participants' assignment of grammatical roles across languages.

Input language and stimuli

The artificial languages used in the experiment contain 8 nouns (4 animate, 4 inanimate), 3 transitive verbs, 1 existential verb, 1 interrogative pronoun (who/what), and an optional argument marker. The languages have flexible word order, in which the verb always comes at the end of the sentence, but the subject noun and object noun appear in free variation (50% SOV and 50% OSV). The optional argument-marking suffix only appears in 50% of transitive sentences, and appears equally often for both word orders, animacy noun types, and information structure noun types. The argument-marking suffix marks direct objects in the DOM language and subjects in the DSM language.

Both animate and inanimate nouns appear equally as either the agent or the patient in transitive phrases. Each noun appears in transitive phrases paired with every other noun an equal number of times. This yields four types of transitive events (Figure 2), three of which are atypical. Each event comprises 25% of the stimuli. Each transitive event could be described using four different constructions, either SOV or OSV without marking (and therefore ambiguous), or SOV or OSV with marking.

In addition to its animacy assignment, each argument is assigned an information structure status for each event: one argument is given in the discourse and one argument is new and in focus. This is done by introducing one noun with a context sentence using an existential construction (X ∃ "there is X"), followed by a transitive event featuring the noun as an actor along with an interrogative construction (Q X V "what/who does X Verb?" or "who/what Verb X?"), before finally showing the complete transitive sentence (X Y V or Y X V, where X is given and Y is new). Accordingly, a specific transitive event occurs in two contexts (Figure 3): either the agent is given and the patient is new (typical), or the patient is given and the agent is new (atypical). A specific unmarked sentence is therefore used to describe two transitive events in two possible contexts yielding four possible scenarios, while marked sentences are used to describe a single transitive event in two contexts yielding two possible scenarios.

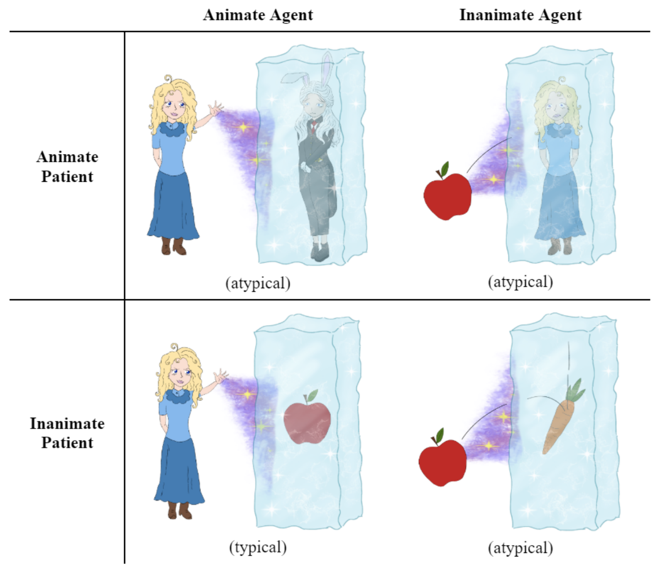

Figure 2: Examples of the four types of transitive events based on the animacy of their arguments.

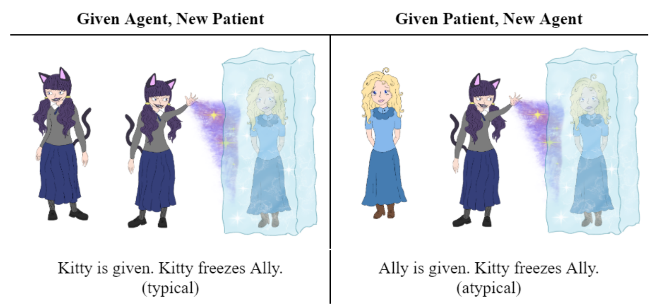

Figure 3: Examples of the two contexts for a specific transitive event.

Procedures

The experimental procedures were adapted from those described by Tal et al. (2022).

1. Noun training (Days 1-3): In each trial, the participants were shown a picture of a person or object along with the corresponding noun in the artificial language. Next to the picture were two buttons, one being the correct corresponding label, another being a randomly selected label. The participant had to click the correct label. Feedback was provided after each trial, and trials where participants clicked on the wrong labels were repeated until they were correct. Participants received 16 such trials (two for each noun).

2. Noun comprehension test (Days 1-3): In each trial, the participants were presented with two pictures of nouns (either a person or an object) and an existential phrase featuring

the noun label in the artificial language. Participants had to choose the correct picture that matched the label and were provided feedback. Participants progressed to the next trial regardless of their success or failure. Participants received 8 such trials (one for each noun).

3. Sentence training (Days 1-3): In each trial, the participant was presented with an existential sentence in the artificial language featuring the label of a noun (There is an X) along with four different pictures of nouns. The participant had to click the correct picture and feedback was given. After selecting a picture for the existential sentence, the participant was then given a transitive sentence and a picture of the corresponding transitive action using the noun from the previous existential sentence as one of its arguments. At the bottom of the picture, the participant was provided with three labels corresponding to each word in the sentence. Labels always appeared without marking regardless of whether the sentence had argument marking. The participant was required to click the label corresponding to the action (the verb). Finally, the participant was presented with a question in the artificial language using the interrogative pronoun, representing the argument that did not appear in the existential construction. The participant had to then click the label corresponding to the interrogative pronoun to answer the question. Participants received 48 such trials.

4. Noun training (Days 1-3): Same as the first procedure.

5. Noun comprehension test (Days 1-3): Same as the second procedure.

6. Sentence comprehension test (Day 3): This phase appeared only on the last day of the experiment. In each trial, the participant was presented with a dialogue starting with an existential sentence featuring the label of a noun (There is an X) and a picture of the noun. The participant was then shown two transitive events that featured the given noun as the agent in one and as the patient in the other, accompanied by an interrogative sentence where the interrogative pronoun corresponds to the other noun in the transitive events. Finally, the complete transitive sentence was given and the participant clicked on the transitive event that they thought best matched the sentence. Participants received 96 such trials.

Participants

Participants were recruited through Facebook, emails, and university classes. They were all native speakers of Estonian. Participants were paid €10 in the form of a gift card at the end of the experiment. 67 participants (DOM: 36, DSM: 31) completed all three days of the experiment. Only participants who completed the entire experiment were included in analyses. This experiment was approved by the research ethics committee of the University of Tartu (ref. 382/T-29).

Results and analysis

R package brms (Bürkner, 2017; R Core Team, 2025) was used to fit a Bayesian linear regression model to data from the unmarked sentence comprehension trials. The model was fitted using a Bernoulli likelihood and a logit link function. Weakly regularizing priors were chosen using prior predictive checks. The model converged, with all $\hat{R}$ values equal to 1.00.

The model estimated the log-odds of an OSV response (as opposed to SOV) for unmarked sentence comprehension based on the following predictors: DAM type (DOM/DSM), animacy order (equal animacy [EA] / animate inanimate [AI] / inanimate animate [IA]), givenness order (given new [GN] / new given [NG]), and interactions between all predictors. Language type was sum-coded (DOM as 1/2 and DSM as -1/2), as was animacy order (EA as -2/3, AI as 2/3, 0, and IA as 0, 2/3), and givenness order (GN as 1/2 and NG as -1/2). The model contained by-participant adjustments to the intercept and to the slopes of animacy order and givenness order, as well as by-target adjustments to the intercept.

Figure 4 shows participants' preference for interpreting OSV word order in unmarked sentences in each context between language groups. Notably, in instances where sentences were presented with given information first, followed by new information, the proportion of OSV responses is low in all animacy conditions for both groups. Conversely, in instances where sentences were presented with new information first followed by given information, the proportion of OSV responses is more evenly distributed. Additionally, the proportion of OSV responses appears more evenly distributed under the inanimate-first condition and more skewed to lower proportions under the animate-first condition.

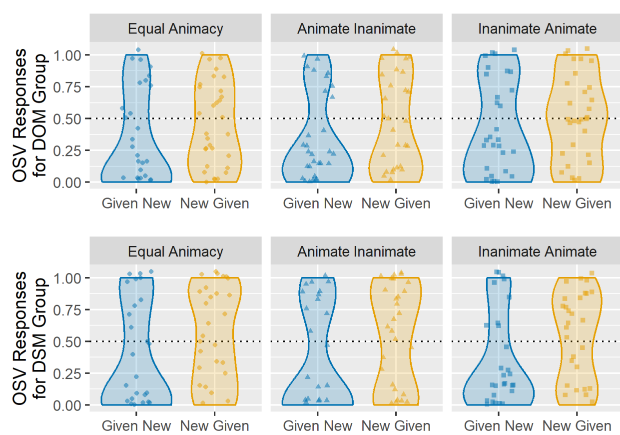

Figure 4: Each participant's mean OSV responses in argument structure assignment during unmarked sentence trials in comprehension tests for different contexts (given-new order vs. new-given order; equal animacy vs. animate-inanimate order vs. inanimate-animate order) across language types. The horizontal dotted line indicates chance.

The posteriors of the unmarked sentence comprehension model are summarized in Table 1 and visualized in Figure 5. The model's intercept reflects the grand mean, i.e., the overall log-odds of an OSV interpretation. With a posterior mean of -0.75 and a consistently negative 95% credible interval spanning [-1.37, -0.15], the model suggests an overall bias against

OSV with 95% certainty. In other words, the participants show an overall bias for the SOV interpretations of unmarked sentences (a log-odds of 0 would indicate no bias, that is, a 50% probability of OSV interpretations).

Table 1: The posterior means and 95% credible intervals (CrI) for the fixed effects of the unmarked sentence comprehension model, given in log-odds space.

	Posterior Mean	95% CrI
Intercept	-0.75	-1.37, -0.15
DAM (Language)	-0.15	-1.39, 1.05
A-Order=AI	-0.22	-0.59, 0.12
A-Order=IA	0.28	-0.09, 0.65
G-Order	-1.17	-1.96, -0.41
DAM * A-Order=AI	-0.03	-0.70, 0.67
DAM * A-Order=IA	0.46	-0.27, 1.19
DAM * G-Order	0.52	-0.96, 2.00
A-Order=AI * G-Order	-0.11	-0.60, 0.39
A-Order=IA * G-Order	0.11	-0.37, 0.58
DAM * G-Order * A-Order=AI	0.20	-0.74, 1.14
DAM * G-Order * A-Order=IA	0.25	-0.66, 1.18

Among the posteriors of the predictor coefficients, only the givenness order condition shows a 95% credible interval that is entirely to one side of zero. With regard to givenness, typicality would predict that given information would be more associated with subjects while new information would be more associated with objects; in other words, given-new order should be associated with more SOV interpretations while new-given order should be associated with more OSV interpretations (a negative effect). The mean of the givenness order parameter's posterior is -1.17 log-odds (95% CrI: [-1.96, -0.41]) with the 95% credible interval comprising only negative values. This suggests that there is a 95% probability that this effect is negative–and rather large–when all other predictors are at their means. In other words, it is highly probable that new-given order results in more OSV interpretations as predicted by typicality.

With regard to animacy, typicality would predict animate actors to be more associated with subjects and inanimate actors to be more associated with objects; in other words, animate-inanimate word order should be associated with more SOV interpretations (a negative effect) while inanimate-animate word order should be associated with more OSV interpretations (a positive effect). The posterior mean of the animacy order parameter comparing animate-inanimate order to other orders is -0.22 log-odds (95% CrI: [-0.59, 0.12]), while the posterior mean of the animacy order parameter comparing inanimate-animate order to other orders is 0.28 log-odds (95% CrI: [-0.09, 0.65]). Notably, the trends in the posteriors of these parameters mirror each other and largely reflect what is predicted by typicality. However, while there is notably

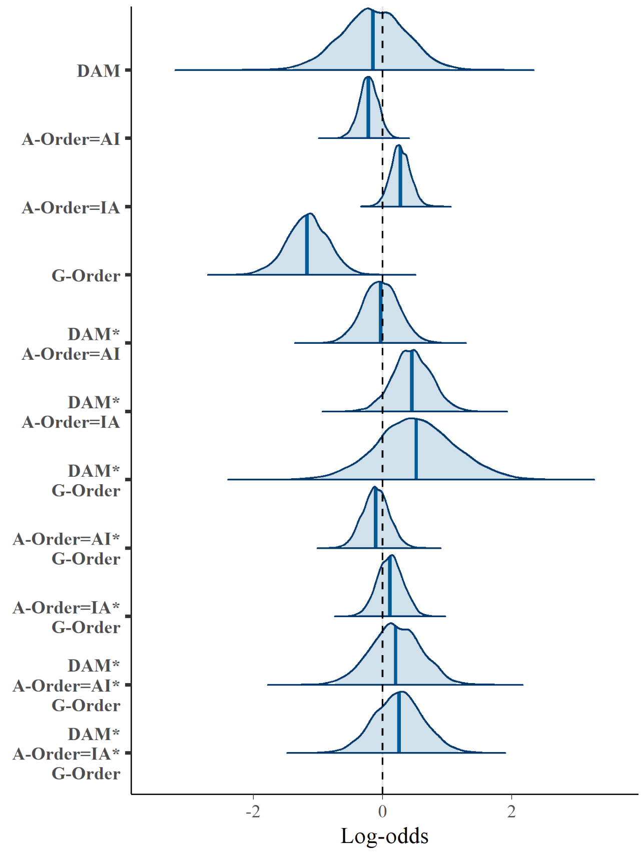

Figure 5: Posterior distributions of the unmarked sentence comprehension model's slope coefficients. Blue vertical lines represent posterior means, and the shaded regions cover the 95% credible interval. Only the credible interval for the givenness order effect is fully on one side of zero indicating that the model is 95% certain that new-given order is associated with greater OSV responses. None of the other predictors are fully on one side of zero indicating uncertainty about their relationship with the outcome.

more posterior probability mass to one side of zero for both parameters with quite narrow credible intervals, the fact that their intervals still contain zero means that the model considers null effects, or even reverse effects, to also be plausible. Despite this, if the negative effect of animate-inanimate order and positive effect of inanimate-animate order are taken to be credible, their effects are likely quite small relative to that of the givenness order condition.

With regard to the DAM language type, the posterior mean is centered close to zero (-0.15 log-odds) with a very wide credible interval (95% CrI: [-1.39, 1.05]). In other words, the model did not find a clearly positive or negative difference in OSV interpretations between the DOM language and the DSM language. Similarly, the posteriors of all interaction effects either contain zero or are centered around zero and exhibit broad credible intervals reflecting high uncertainty.

Discussion

Our hypothesis predicted that participants would rely on typicality when assigning grammatical roles in unmarked sentences, relying on information structure and the animacy of the arguments. The data support this, where there is a clear, large effect of givenness (i.e., given-first results in more SOV, new-first results in more OSV) and a plausible yet smaller effect of animacy (i.e., animate-inanimate results in more SOV, inanimate-animate results in more OSV). Additionally, there appears to be no notable differences between the results of the DOM group and that of the DSM group. This suggests that type of marking learned does not affect a listener's reliance on typicality biases for disambiguation in unmarked sentences. Given these results, it is reasonable to expect speakers of languages with DOM or DSM to employ marking in atypical situations to overcome these typicality biases.

Typicality-based DAM as a communicative phenomenon

In light of these results and prior production studies (e.g., Smith & Culbertson, 2020), it seems plausible that typicality-based DAM emerges through communication. In one-sided production, speakers do not receive feedback on whether their utterance was understood by an interlocutor and thus have no incentive to mark atypical situations. Rather than considering the plausibility of meanings behind their production, they adjust their production according to successful communication. Listeners, by contrast, assume communicative intent and interpret signals based on plausibility of meanings (i.e., typicality). While not directly tested in our design, it is reasonable to expect that speakers learn which signals are more successful in which contexts through interactions with listeners. In other words, typicality-driven DAM is expected to arise in communication, where speakers employ marking to override listener biases that might otherwise lead to misinterpretation.

The effect of givenness vs animacy

One of the most striking results of this study is the magnitude of the effect of givenness, particularly relative to animacy. We propose two ways to interpret this result. It may be the case that givenness is a more general, omnipresent phenomenon, in which agents in the real world are more frequently given than necessarily animate and patients more frequently new than inanimate. If this is the case, a much stronger typicality bias based on givenness is plausible and is consistent with cross-linguistic tendencies in DOM (Iemmolo, 2010, 2020). Alternatively, it may be the case that givenness is inherently more abstract and less perceptually salient than animacy, meaning that—even though givenness received explicit emphasis in training—participants might still have been less consciously aware of it as a factor influencing their expectations. In other words, the animacy of the arguments is concrete and more obvious, so the participants would be more sensitive in adjusting their expectations to match the input, thus dampening the effects of any real-world biases. Participants' expectations towards givenness, however, would retain more of their real-world biases and lead to larger effects. These explanations are not mutually exclusive.

The effect of DOM vs. DSM

Interestingly, the results show no difference between the DOM and DSM groups—neither in typicality effects nor in overall word order preferences. While it may seem odd to expect marking to influence the interpretation of unmarked sentences, similar effects have been observed in production (Fedzechkina et al., 2012), where DOM leads to more marked OSV and unmarked SOV utterances, and DSM leads to more marked SOV and unmarked OSV. This has been interpreted as a bias to mention disambiguating information first—placing the marked argument first in marked utterances and the other argument type first when unmarked. However, this effect appears to be absent in comprehension, where typicality biases drive word order interpretation regardless of the type of marking learned.

Limitations and future directions

Future research should explore diverse linguistic backgrounds to replicate and validate these findings across different populations and to assess the robustness of the observed biases. The frequency of input stimuli can also be tested to assess how participants' typicality biases are affected by training. Additionally, interactive communication tasks should be used to test real-time speaker-side adaptation to the listener's biases for both animacy and givenness, and to test for potential non-communicative production biases that may affect DSM and DOM differently. Tal et al. (2022), for example, have already demonstrated a potential non-communicative tendency in production to front and mark given/topical objects with DOM; it may be the case that this tendency extends to given/topical arguments in general, thus accounting for the prevalence of 'exceptional' DSM systems. Finally, other diachronic processes in the emergence of DAM regarding the source of linguistic material employed in marking, such as metaphorical extension and reanalysis, should also be taken into consideration and tested experimentally.

Conclusion

This study demonstrates how listeners rely on typicality biases (especially information structure) to interpret ambiguous sentences in artificial languages with DAM. In conjunction with evidence from production studies (Fedzechkina et al., 2012; Tal et al., 2022; Smith & Culbertson, 2020), these results suggest that typicality-based DAM is best understood as a communicative phenomenon. Furthermore, givenness appears to have a stronger effect than animacy in determining the grammatical roles of arguments in unmarked sentence comprehension. Both DOM and DSM learners show similar comprehension biases, suggesting other factors beyond typicality are needed to account for the disparity between the parameters governing DOM and DSM systems in natural languages.

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