Bayesian and Random Forest Models of Morphosyntactic Variation: Accusative vs. Dative Clitics in Spanish Causative Constructions

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Abstract: In Spanish causative constructions with *dejar* 'let' and *hacer* 'make' the subject of the embedded infinitive verb can appear in the accusative or the dative case. This case alternation has been accounted for by resorting to the notion of direct vs. indirect causation. Under this account, the accusative clitic with a transitive verb denotes direct causation while the dative clitic with an intransitive verb expresses indirect causation. The problem with this account is that we lack an independent definition of (in)direct causation in this context and so this approach suffers from circularity: the case of the clitic is used to determine causation type and causation type implies use of one or the other grammatical case. Therefore, a more objective way to account for clitic case alternation is needed. In this paper, I offer one possible solution in this direction by investigating clitic case alternation against Hopper and Thompson's Transitivity parameters and a small number of other linguistic variables. The analysis is conducted on a dataset of 4,589 sentences analysed with Bayesian mixed-effects models and a large random forest. The results indicate that the transitivity of the infinitive verb, the animacy of the object and the agentivity of the subject are strong predictors of clitic case but there are also important dialectal differences. The findings in this paper allow us to arrive at a finer-grained characterization of the contexts in which each case is more likely to occur and provide further evidence of the pervasiveness of Transitivity in natural language.

1 Introduction

Spanish lacks overt case marking on noun phrases (NPs) but the pronominal system still shows some vestiges of case marking. This is clearly the case with third-person pronominal elements, which distinguish between nominative (1a), accusative (1b) and dative cases (1c). I refer to them as pronominals because, technically speaking, the nominative set comprises true pronouns whereas the accusative and dative sets are made up of clitics.

1a. **Él** corrió.

he ran.3S.

'He ran'

1b.	Ella	**lo**	vio.
	she	him.ACC	saw.3S
	'She saw him'		
1c.	Ella	**le**	gritó.
	she	him.DAT	screamed.3S
	'She yelled at him'		

Generally speaking, nominative marks the subject of the sentence, accusative the direct object of a transitive verb and dative case is used for the indirect object. However, this one-to-one mapping between grammatical function and case marking does not always obtain. For example, with reverse-psychological predicates such as *asustar* 'to frighten' or *molestar* 'to bother' the experiencer argument can appear in either the accusative (2a) or the dative case (2b).

2.	a.	Las	víboras	**lo**	asustan.
		the.fem.pl	snakes	him.acc	frighten.3pl
		'Snakes scare him.'			
	b.	**Le**	asustan	las	víboras.
		him.dat	frighten.3pl	the.fem.pl	spiders
		'Snakes scare him.'			

Several analyses have attempted to characterize and account for the case alternation exhibited in (2). Some have argued that it depends on the eventuality denoted by the sentence [1] and others that Transitivity factors are key in determining the case of the clitic [2], [3], [4], [5]. The findings suggest that accusative marking is more likely with high Transitivity contexts such as agentive subjects, telic predicates and affected objects. In contrast, dative marking is most likely found with stative and atelic predicates, non-agentive subjects and non-affected objects.

Another construction where the clitic case alternation is found is with the causative predicates *dejar* 'to let' (3) and *hacer* 'make' (4).

3. | **Lo/ le** | dejan | correr | afuera. |
|---|---|---|---|
| him.acc/ him.dat | let.3pl.pres | run.inf | outside |

‘They let him run outside.’

4. | **La/ le** | hacen | caminar | mucho. |
|---|---|---|---|
| her.acc/ her.dat | make.3pl | walk.inf | much |

‘They make her walk a lot.’

The case alternation in this construction has attracted a lot of attention in the literature. The first accounts argued that the alternation could be explained by whether the infinitive verb was transitive or intransitive; transitive verbs require dative marking and intransitive verbs accusative case [6], [7]. This pattern was not only found in Spanish but it’s a more general characteristic cross-linguistically [8]. Despite the appeal for its simplicity and cross-linguistic coverage, this account cannot capture some data in Spanish where the opposite case appears to the one that would be expected. That is to say, it is not uncommon in spontaneous production to find examples of transitive verbs with accusative clitics (5) and intransitive verbs with dative clitics (6) (e.g., [9] and references therein). Note that the name of the country in the examples indicate the country where the sentence is found in the corpus; the number indicates the ID in the dataset.

5. | Los | bancos | no | lo | dejaban | resolver |
|---|---|---|---|---|---|
| the.MASC.PL | banks | not | him.ACC | let.3PL.PAST | solve.INF |

la	crisis
the.FEM.SG	crisis

‘The banks wouldn’t let him solve the crisis’

(Colombia: 4380)

6. La tos no le deja dormir

the.FEM.SG cough not him.DAT let.3S sleep.INF

'The cough doesn't let him sleep.'

(Mexico: 1536)

In (5) the infinitive verb *resolver* 'to solve' is transitive so the dative clitic *le* is expected but instead we find the accusative *lo*. In (6) the infinitive verb is *dormir* 'to sleep', a prototypical intransitive verb, and yet the clitic appears in the dative form instead of the expected accusative case. To account for this type of data, researchers have resorted to the semantic notion of (in)direct causation. Under this account, a transitive predicate with an accusative clitic expresses direct causation while an intransitive predicate with a dative clitic denotes indirect causation [9], [10]. This account does not say anything about the type of causation implied when the case of the clitic matches the expected value (i.e., transitive → dative and intransitive → accusative). One issue with this explanation is that it suffers from circularity. That is to say, the case of the clitic is used to determine the type of causation expressed in the sentence and then the claim is that the difference in the grammatical case of the clitic expresses a difference in causation. The reason for this circularity lies in the fact that causation type has not been independently defined to act as a diagnostic for, and explanation of, clitic case. This becomes apparent when nothing can be said about causation type when the clitic matches the expected case. If causation type were an independently defined concept, we should be able to characterize each and every context where causation is called for not only those cases that are 'exceptions'.

This paper is an attempt to offer a more systematic and objective way to account for the case alternation of clitics in causative constructions. Adopting Hopper and Thompson's Transitivity parameters [11] together with other linguistic variables such as TENSE, COUNTRY and CAUSATIVE TYPE, I analyse a dataset of 4,589 sentences. The analysis is conducted within a Bayesian inference framework by means of a mixed-effects logistic regression model that was fit in two different ways: in Model-1 the Transitivity parameters are entered individually as binary categorical variables whereas in Model-2 the parameters are quantified such that a unique Transitivity Score is computed for each sentence. The Transitivity Score is then used as the main predictor in Model-2. To complete the analysis, I provide Model-3, a large random forest with all the variables used in the analysis to determine the relative importance of each variable (see details in the Methodology section).

1.1 The Transitivity Parameters

On the basis of cross-linguistic evidence, Hopper and Thompson [11] propose that transitivity should be construed as a scale that applies at the clause level as opposed to being a property of just the verb. In their view, Transitivity is composed of ten parameters addressing features of the subject, verb and object of the clause as shown in Table 1. All the parameters are binary except for INDIVIDUATION, which describes features of the object and is made up of the six sub-parameters in Table 2.

Table 1. Hopper and Thompson's Transitivity Parameters.

Component	High	Low
PARTICIPANTS	2 or more	1
KINESIS	action	non-action
ASPECT	telic	atelic
PUNCTUALITY	punctual	non-punctual
VOLITIONALITY	volitional	non-volitional
AFFIRMATION	affirmative	negative
MODE	realis	irrealis
AGENCY	A high in potency	A low in potency
AFFECTEDNESS OF O	totally affected	not affected
INDIVIDUATION OF O	highly individuated	non-individuated

Table 2. The subparameters comprising INDIVIDUATION

Individuated	Non-Individuated
proper	common
human, animate	inanimate
concrete	abstract
singular	plural
count	mass
referential, definite	non-referential

As the tables show, each parameter has a value that corresponds to higher Transitivity and the opposite value that corresponds to lower Transitivity. For example, for the PARTICIPANTS parameter, a transitive verb (2 participants) is higher in Transitivity than an intransitive verb with only 1 participant. The appeal of this approach is that clauses can be categorized in a scale as more or less transitive instead of relying on a categorical distinction solely based on the transitivity status of the verb.

Transitivity can be seen at play in a variety of languages across different linguistic phenomena. For example, in the language Yukulta irrealis clauses mark the object with oblique case instead of the usual absolutive case in realis clauses [12]. In Estonian, partitive case is used instead of the accusative and genitive cases to mark the partial degree of affectedness of the object [13]. In English, Transitivity has been used to account for properties of implicit objects (e.g., John cooked [∅] this morning) distinguishing between indefinite and definite readings of this construction [14] (for a detailed account of Transitivity cross-linguistically see [11]).

In Spanish, Transitivity has been useful in accounting for differential object marking [15], non-anaphoric uses of the clitic *se* [16], inalienable possessive constructions [17] and reverse-psychological predicates [5], [2], among others.

There has been some previous work using features similar to the Transitivity parameters in the study of clitic case alternation with causatives, but to the best of my knowledge, this is the first article using a combination of statistical models and the Transitivity parameters to account for clitic case alternation in causative constructions. Enghels [10] studies the case alternation of clitics in the causative constructions with *dejar* and *hacer* in Peninsular Spanish with corpus data. She analyses 500 sentences with a number of linguistic variables such as causative (*dejar* 'let' or *hacer* 'make'), dynamicity of the object and subject (animate, dynamic inanimate, non-dynamic inanimate) and the type of infinitive verb (transitive, unergative and unaccusative). She finds a number of differences between the realization of dative and accusative case. For example, it is reported that in general both causatives appear much more with the dative than with the accusative case and animate objects also tend to favour the dative clitic. On the other hand, the chances of finding the dative case drop as the dynamicity of the infinitival complement increases (i.e., the more dynamic the predicate, the less likely it is to find the dative clitic). With respect to the dynamic aspect of the subject, she finds an interesting dichotomy between the two causatives; very dynamic subjects with non-dynamic objects favour the accusative case with *hacer* but dynamic subjects with *dejar* are found with the dative clitic. In addition, her data show that the more dynamic objects also favour the dative clitic while abstract inanimate objects are more often found with the accusative.

An important difference between the present study and the study described above is that Enghels [10] only studied Peninsular Spanish. Studying clitic case alternation in Peninsular Spanish is problematic because *leísmo*, the phenomenon where the dative clitic *le* is used for masculine animate *direct* objects, is very prevalent in this variety [18], [19]. This phenomenon makes it difficult to determine the case of the clitic because the realization of the clitic as *le* cannot be unambiguously interpreted as signalling dative case when the referent is animate and masculine. To avoid this issue, Peninsular Spanish is not included in the present study. On the other hand, the results of Enghels's study allow us to make very precise and testable predictions that can be evaluated in our models.

1.2 Hypotheses and predictions

Based on the results of Enghels's study and Hopper and Thompson's parameters, the following hypotheses and predictions were tested.

Hypothesis 1: The Transitivity parameters will co-vary in the same direction

Hypothesis 2: The two causative predicates will show different preferences in clitic case.

Hypothesis 3: Accusative case will align with higher Transitivity and dative case with lower Transitivity.

Hypothesis 1 falls out from Hopper and Thompson's proposal that the parameters should co-vary towards the same end of the scale. This means, for example, that if a language makes a distinction between telic and atelic predicates and between definite and indefinite objects, then they predict that telic predicates should co-occur with definite objects and atelic ones with indefinite objects. Hypothesis 2 follows from Enghels's work where she finds that *hacer* appears with the dative case more often than *dejar.* If this is a general characteristic of the construction, then we predict that the Bayes factor for the variable CAUSATIVE will show positive evidence in favour of this hypothesis and the posterior mean estimate will be positive (because *Accusative* and *dejar* are the reference levels). Hypothesis 3 follows from previous work both on causatives and reverse-psychological predicates where accusative was found to occur in higher transitivity contexts [2], [20], [5]. If accusative is associated with higher transitivity, then we expect that as transitivity increases, the probability of the accusative will increase and that of the dative will decrease. Model-2 will allow us to test this prediction.

2. Methodology

2.1 Data and variable coding

The data were extracted from Corpus del Español [21] Web Dialects and NOW (News on the Web) versions. The web interface of the corpus only allows for extraction of a maximum of

1000 hits per search so 1000 hits for each clitic were extracted from the Web Dialects. As the dative clitic only inflects for number but not for gender this resulted in twice as many accusative clitics than dative clitics. In order to have a more balanced data set, 2000 more sentences with the dative clitic were extracted from the NOW corpus (1000 singular and 1000 plural). Both versions of the corpus are made up of texts from the Internet so the register is relatively similar in both; the NOW corpus contains mostly news and the Web Dialects contains news, general websites and blogs. After removal of duplicates and false positives, the dataset contains a total of 4589 sentences from 19 Spanish-speaking countries.

The annotation of the data was conducted manually using the Transitivity parameters as well as four additional variables. Table 3 shows all the variables used and the possible values of each. Not all of Hopper and Thompson's parameters were considered, however. VOLITIONALITY being almost indistinguishable from AGENCY was discarded and only AGENCY was included. For the INDIVIDUATION parameters, REFERENTIAL was not included because most objects were referential in this construction and there were no proper nouns in the sample so *proper* vs. *common* was not included. The four added variables are TENSE, PERSON, NUMBERSUBJ and GROUP. The first three of these variables refer to grammatical features of the causative. Due to data sparsity (i.e., very few data points of some levels of a variable) TENSE and PERSON were coded as binary variables. TENSE was coded as past vs. non-past and PERSON as 3rd vs. non-3rd. NUMBERSUBJ refers to the number feature of the subject of the causative verb (singular vs. plural). The variable GROUP corresponds to two groups comprising the country where the sentence was found according to the corpus. The grouping of the countries was done after fitting a conditional inference tree with the `party` package [22] with COUNTRY as a predictor variable with the 19 countries as levels and CASE as the dependent variable. The tree is shown in Fig 1. I chose the two larger groups that were found by the algorithm so the countries were divided into two groups. Group 1 comprises Bolivia, Chile, Ecuador, Nicaragua, Peru, Puerto Rico and Paraguay and Group 2 is made up of Argentina, Colombia, Costa Rica, Cuba, The Dominican Republic, El Salvador, Guatemala, Honduras, Mexico, Panama, Uruguay and Venezuela.

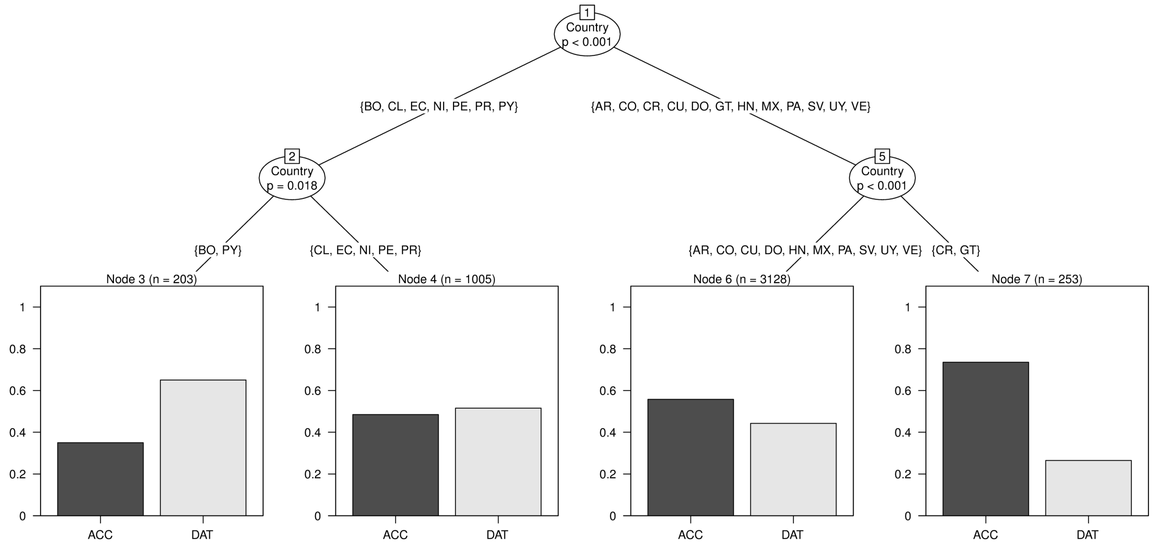

Fig 1. Conditional inference tree with seed 135 with Case as the dependent variable and Country as the only predictor variable.

Table 3. Predictor variables and possible values of each.

Variable Name	Possible Values	Variable name	Possible Values
AFFECTEDNESS	*affected/ non-affected*	MODE	*indicative/ subjunctive*
AFFIRMATION	*affirmative/ non-affirmative*	NUMBER_OBJ	*sg/ pl*
AGENCY	*high/ low*	NUMBER_SUBJ	*sg/ pl*
ANIMATE	*animate/ inanimate*	PARTICIPANTS	*transitive/ intransitive*
ASPECT	*telic/ atelic*	PERSON	*3rd/ non-3rd*
CAUSATIVE	*dejar/ hacer*	PUNCTUALITY	*punctual/ non-punctual*
CONCRETENESS	*concrete/ abstract*	TENSE	*past/ non-past*
COUNT	*count/mass*	TRANSITIVITY_SCORE	*continuous between 0-1*
KINESIS	*state/ non-state*	GROUP	*Group 1, Group 2*

After the data was coded, a new variable TRANSITIVITY SCORE was calculated. The formulas for the calculation of the score are in Equation 1 and 2. This score was computed from numerical values of the Transitivity parameters. Each high Transitivity level was given a value of 1 and each low Transitivity level was given a value of 0. Then all the values per sentence were added up and the result was divided by the total number of parameters, which is 9 in our case so that the score ranges from 0-1. Since INDIVIDUATION comprises 4 subparameters, the value of this parameter was first computed from adding up the values of the subparameters and dividing it by four. Then this result was used to calculate the total Transitivity Score.

$$\text{Individuation Score} = \frac{(\text{ANIMACY}+\text{CONCRETENESS}+\text{NUMBER\_OBJ}+\text{COUNT})}{4}$$

Equation 1. Formula for Individuation Score

$$\text{Transitivity Score} = \frac{(\text{PARTICIPANTS} + \text{KINESIS} + \text{TELICITITY} + \ldots + \text{INDIVIDUATION})}{9}$$

Equation 2. Formula for Transitivity Score.

2.2 Statistical Analysis

The statistical analysis was conducted in R 3.6.3 [23]. As I explained above, the countries were first grouped by fitting a conditional inference with CASE as the dependent variable as COUNTRY as the predictor variable. The conditional inference tree was fitted with the `party` package [22] with random seed 135.

Two Bayesian mixed-effects logistic regression models were fitted with the Stan modelling language [24] in the `brms` package [25]. Four sampling chains ran for 3000 iterations each with a warm-up period of 1500 iterations, thereby resulting in a total of 6000 samples for each parameter tuple. I followed the recommendations in Gelman et al. [26] for the choice of prior distributions and scaled the continuous variable in Model-2 to have a standard deviation of 0.5. For the fixed effects, I used a Cauchy weakly informative prior distribution with centre 0 and scale 2.5 (0, 2.5) and the intercept has a scale of 10 (0,10). This Cauchy distribution prior on the fixed effects gives preference to values less than 5 but it also allows for the possibility (25%) of very large values should the data show evidence for this [26]. For the prior distribution on the random effects, I used the default setting in the `brms` package, namely a Student's *t*-distribution ($v = 3$, $\mu = 0$, $\sigma = 10$).

Model-1 is a Bayesian mixed-effects logistic regression fitted with the Transitivity parameters individually such that each parameter can contribute separately to the model. In addition, the four extra variables TENSE, PERSON, NUMBERSUBJ and GROUP were included in the model. The model was fitted with a number of interactions based on findings from the literature, namely AGENCYSUBJ*ANIMACYOBJ, PARTICIPANTS*CAUSATIVE, PARTICIPANTS*AGENCYSUBJ, AGENSYSUBJ*CAUSATIVE, CONCRETENESS*PARTICIPANTS, COUNT*PARTICIPANTS and GROUP*PARTICIPANTS. The effect of each predictor variable was tested by means of Bayes factors. A null region was first calculated with the `bayestestR` package. A null region is an interval that is practically equivalent to 0. This means that if the posterior distribution of a predictor falls within this region, we cannot assert that there is evidence against the null hypothesis. The Bayes factor computes the posterior odds of the posterior probability within the null region and the posterior probability outside the null region. The interpretation of Bayes factors is as follows [27]: BF < 1 evidence in favour of the null hypothesis (the parameter does not contribute to explaining the outcome), BF = 3-10 there is moderate evidence, BF = 10-30 there is strong evidence, BF = 30-100 there is very strong evidence and BF > 100 extreme evidence. A Bayes factor lower than 1 represents evidence in favour of the null hypothesis and a Bayes factor of one

Model-2 is also a Bayesian mixed-effects logistic regression but the main predictor variable is TRANSITIVITY SCORE. The other four variables were also included in the model so that both models could be compared on the same predictor variables.

Besides looking at the posterior distributions of the models to study the evidence in favour or against the effect of each predictor variable, I also analyse and compare the predictive accuracy of Model-1 and Model-2 to determine which of the two ways of operationalizing Transitivity has the most predictive power regarding the case of the clitic.

I finish the analysis with Model-3 to calculate the relative importance of each predictor variable by fitting a large random forest with all the predictors. This measure allows us to determine which of the variables studied are the most important in determining the case of the clitic. The random forest was fitted with the `party` package [22] and is composed of 5001 trees with the default *mtry* value of 5 (the minimum number of variables to be considered at each split). Three random forests were fitted to ensure that variable importance was stable as this is a random procedure. The random seeds for each tree were 102, 104, 107.

3. Results

Model-1

Model-1 contains seven single terms and seven interaction terms. The single terms are AFFIRMATION, AFFECTEDNESS, PERSON, NUMBEROBJ, MOOD, KINESIS and NUMBERSUBJ and the interactions are AGENCYSUBJ*ANIMACYOBJ, PARTICIPANTS*CAUSATIVE, PARTICIPANTS*AGENCYSUBJ, AGENSYSUBJ*CAUSATIVE, CONCRETENESS*PARTICIPANTS, COUNT*PARTICIPANTS and GROUP*PARTICIPANTS.

I will first present the results of the Bayes factor analysis that shows which parameters offer substantial evidence in explaining the dependent variable. For an effect to offer at least moderate evidence for its importance, the Bayes factor should at least be 3. This means that none of the predictors that do not participate in interactions (i.e., AFFIRMATION, AFFECTEDNESS, PERSON, TENSE, PUNCTUALITY, MOOD AND NUMBEROBJ) make a significant contribution to explaining the case of the clitic. The parameters for which there is significant evidence to reject the null hypothesis are CAUSATIVE, AGENCYSUBJ, ANIMACYOBJ, PARTICIPANTS, GROUP. COUNT is not deemed important neither in the interaction with PARTICIPANTS nor as a single term. There is evidence for CONCRETENESS in the interaction with PARTICIPANTS.

For ease of exposition, I present the results of the model in two formats. First, I show the posterior distribution intervals of the terms for which there is enough evidence that they contribute to explaining the case of the clitic according to the Bayes factors. The exception to this is the interaction PARTICIPANTS*COUNT, which must be calculated because even though the interaction *per se* is not very informative, PARTICIPANTS is relevant in other interactions and so I cannot remove the interaction from the calculation. Second, I will present the results of the interactions via marginal effects plots because they offer a nice and reader-friendly way to interpret interactions. A complete table of posterior coefficient estimates, standard errors, 95% credible intervals and convergence diagnostics of Model-1 can be found in the Appendix.

Fig 2 shows the posterior distribution intervals of all terms that participate in an interaction. The posterior distribution intervals allow us to see the degree of uncertainty of the posterior estimate. The smaller the credible interval, the more certain we can be that the coefficient estimate lies within that interval. The posterior distribution intervals in Fig 2 show quite a high degree of certainty as they are rather small with three exceptions. The first exception is the interaction PARTICIPANTS*COUNT, whose posterior mean estimate is 0.40 (CI: -1.74, 2.51). We saw that the Bayes factor for this interaction was 0.318, meaning that the data is three times more probable under the null (i.e., 1/0.318). The fact that the credible interval (CI) contains zero corroborates that it is probable that this interaction has a null effect on the outcome. The interaction PARTICIPANTS*CONCRETENESS also shows a relatively larger posterior distribution interval. In contrast with the previous interaction, however, the Bayes factor for this interaction is 5.304, which shows a moderate degree of positive evidence for an effect. The posterior mean is -1.87 (CI: -3.43, -0.40) and we see that the CI does not contain zero, supporting the existence of a real effect. Since the posterior mean is negative, it indicates that transitive verbs with concrete objects disfavour the dative clitic. The large CI (i.e., the higher degree of uncertainty) is likely due to the small number of abstract objects compared to concrete objects in the data (6% vs. 94%). The third posterior distribution interval that looks slightly wider than the rest is PARTICIPANTS. But since PARTICIPANTS is part of three interactions this posterior coefficient estimate is the value of PARTICIPANTS with abstract and mass objects in Group 2. The Bayes factor for this parameter is 7.184, which shows moderate evidence against the null hypothesis. The posterior mean is 2.65 (CI: 0.49, 4.92), indicating that transitive verbs with abstract mass objects in Group 1 favour the dative clitic.

Fig 3 shows the marginal effects of the interaction terms when all other predictors are held at the reference level. In this case, the reference level is the higher transitive value (e.g., PARTICIPANTS = *transitive*, MOOD = *telic*, CONCRETENESS = *concrete*, etc.). The predicted estimate is the median of all drawn posterior samples and the confidence intervals are Bayesian predictive intervals.

Plot (A) shows the interactions PARTICIPANTS*GROUP. This interaction shows that overall, the dative clitic is mostly favoured with transitive verbs but there are small differences between the two groups of countries. Group 2 seems to favour the dative clitic slightly more than Group 1, for which the predicted probabilities for the dative clitic are lower for both types of verbs. For example, with transitive verbs Group 2 has a predicted probability for the dative clitic of 0.76 while that of Group 1 is 0.72. Likewise, for intransitive verbs the predicted median is 0.25 in Group 2 but 0.13 in Group 1.

Plot (B) shows the interaction PARTICIPANTS*AGENCYSUBJ. The posterior mean estimate for this interaction is 0.6 (CI: 0.2, 1.02), indicating that transitive verbs with agentive subjects increase the odds for the dative clitic. This is clear in the plot where this combination of values has the highest predicted probability for the dative clitic at 0.72. Transitive verbs with subjects low in agentivity have a lower predicted probability of 0.58. With intransitive verbs, agency of the subject does not seem to matter as for both agentive and non-agentive subjects the predicted probability is at 0.13.

The next interaction in plot (C) is PARTICIPANTS*CONCRETENESS. We noted above that this interaction has a higher level of uncertainty due to the relative low number of abstract objects in the sample. The interaction seems to be driven by the way intransitive verbs interact with the concreteness status of the object. With concrete objects, intransitive verbs have a slightly higher predicted probability for the dative clitic at 0.13 compared to 0.025 with abstract objects. Transitive verbs show a very similar behaviour with both types of object with a predicted probability for both at around 0.73.

In plot (D) we can see the interaction CAUSATIVE*AGENCYSUBJ. We can observe that the main difference lies in the causative *hacer* 'make' with subjects low in agentivity; while with subjects high in transitivity *hacer* favours the dative clitic at 0.72, with a subject lower in agency this probability goes down to 0.58. On the other hand, *dejar* has a slightly higher prevalence for the dative clitic with subjects low in agentivity with a predicted probability of 0.74 compared to 0.70 with agentive subjects. Though this difference is indeed rather small, the two causatives seem to show a slightly different behaviour regarding the case of the clitic.

Finally Plot (E) shows the interaction AGENCYSUBJ*ANIMACYOBJ. This interaction shows a clear contrast between agentive (high) and non-agentive subjects (low). What this shows is that when all the other predictors have the higher Transitivity value, subjects high in agency that appear with inanimate objects have the highest predicted probability for the dative clitic at 0.73; when the object is animate this goes down to 0.19. On the other hand, subjects low in agency with animate objects have a predicted probability of 0.58 and 0.35 with animate and inanimate objects, respectively.

Table 4. Bayes factor results indicating the posterior log odds against the null hypothesis of no effect of each predictor. The larger the Bayes factor, the more evidence against the null hypothesis. The shaded areas show Bayes factors larger than 1.

Parameter	BF	Parameter	BF
Affirmation	0.82	AnimacyObj	28.604
Affectedness	0.597	Participants	7.184
Causative	12051.2	Concreteness	368.36
Telicity	0.05	Count	0.108
Tense	0.016	Group	1462.038
Punctuality	0.046	AgencySubj*AnimacyObj	650.141
Person	0.043	Causative*Participants	0.413
NumberObj	0.014	AgencySubj*Participants	2.261
Mood	0.015	Causative*AgencySubj	39.918
Kinesis	0.052	Participants*Concreteness	5.304
NumberSubj	0.257	Participants*Count	0.318
AgencySubj	344700	Participants*Group	1.282

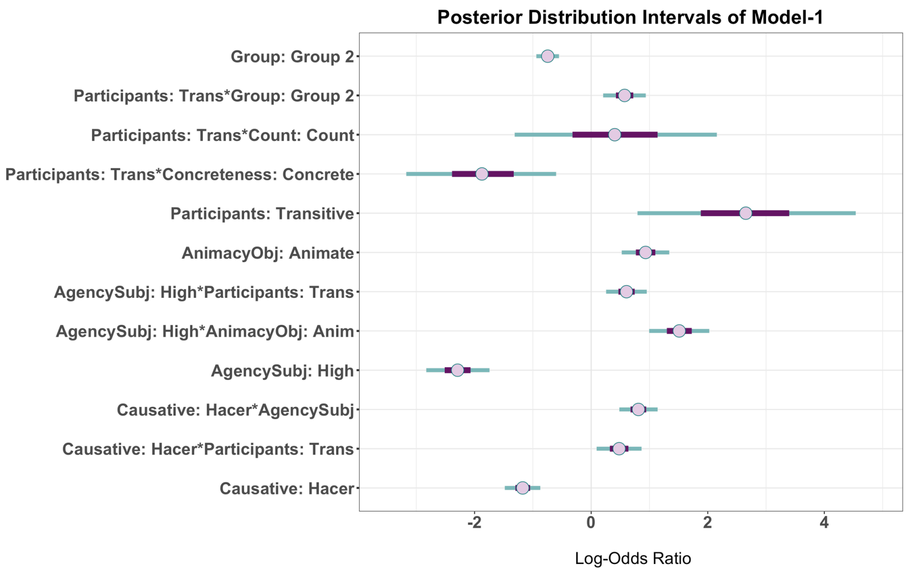

Fig 2. Posterior distribution intervals of terms with a Bayes Factor larger than 1 in Model-1. The thicker purple lines show 50% and the thinner teal lines 90% credible intervals. The dot represents the posterior mean estimate.

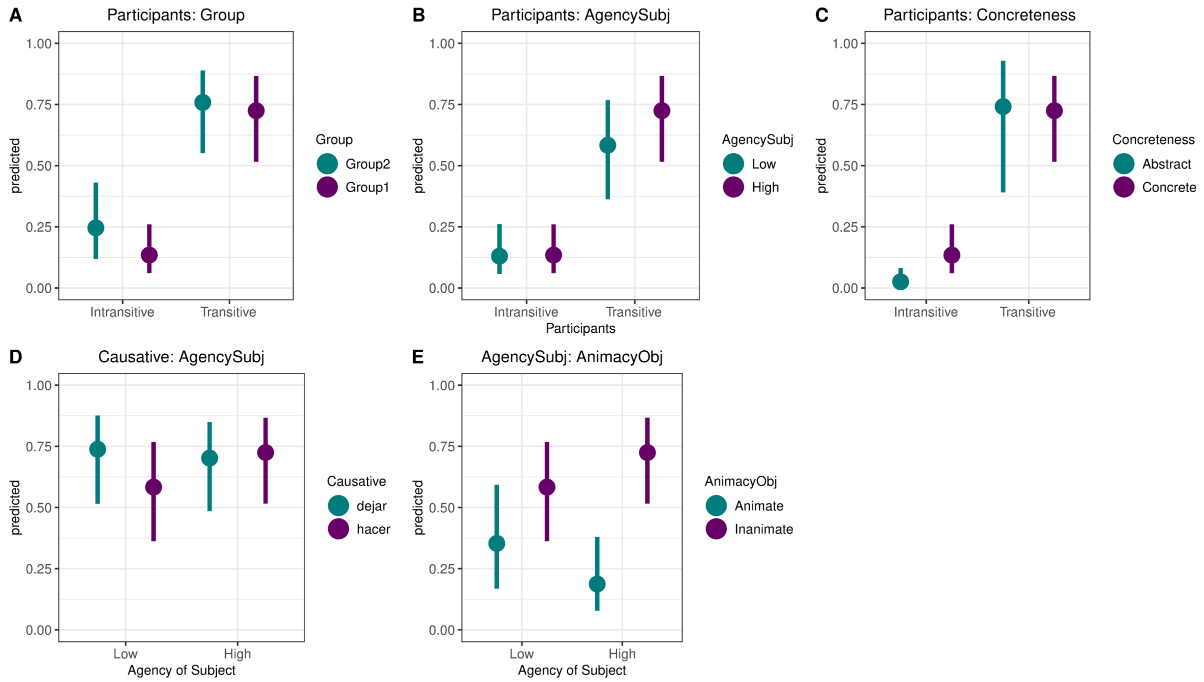

Fig 3. Marginal effects of Model-1. The y-axis represents the posterior predicted probability of the dative clitic when all the other predictors are held at their reference level.

Model-2

Model-2 comprises the Transitivity score as the main predictor of interest and the four extra variables that were also part of Model-1. Fig 4 shows the posterior distribution intervals of the predictor variables. The posterior mean estimate of Transitivity is 0.87 (CI: 0.60, 1.13) suggesting that an increase of one unit in Transitivity increases the log-odds of the dative clitic. This can be clearly seen in Fig 5 that shows the marginal effects of Transitivity. The line colours show the posterior predicted probabilities for the accusative (purple) and dative (green) clitics for two different sets of values of the reference levels of the other four predictors. For Set 1 the predictors are held at PERSON: *non-3rd*, TENSE: *non-past*, CAUSATIVE: *hacer*, NUMBERSUBJ: *singular*. The opposite values of each predictor are represented in Set 2. We can observe a relatively big difference between these two conditions. Although in both conditions the posterior predicted probability for the dative clitic goes up and that of the accusative goes down as Transitivity increases it is clear that the increase is larger for the reference levels of Set 2 (i.e., PERSON*: 3rd*, TENSE: *past*, CAUSATIVE: *dejar*, NUMBERSUBJ: *plural*). In fact, across all levels of Transitivity Set 1 always shows a lower predicted probability for the dative clitic compared to Set 2 and the opposite is true for the accusative clitic. For the higher Transitivity levels, there is a 50% chance of either clitic. In addition, the Bayes factor for the Transitivity score is 1620 demonstrating that Transitivity is an extremely strong predictor for clitic case. The only two other variables that showed evidence of an effect against the null hypothesis in Model-2 were PERSON (BF = 4292) and GROUP (BF = 840).

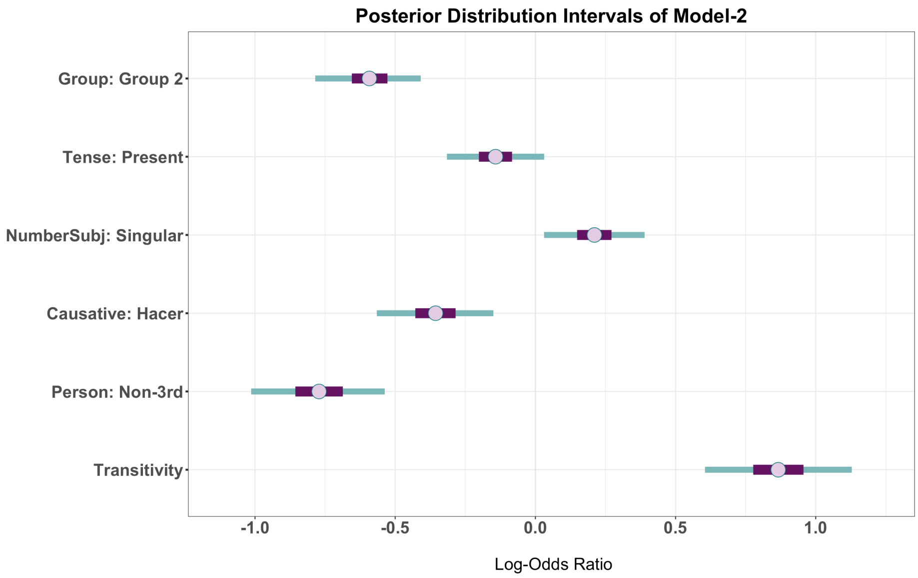

Fig 4. Posterior distribution intervals of Model-2. The dot represents the posterior mean estimate. The thicker purple lines show 50% and the thinner teal lines 90% credible intervals, respectively.

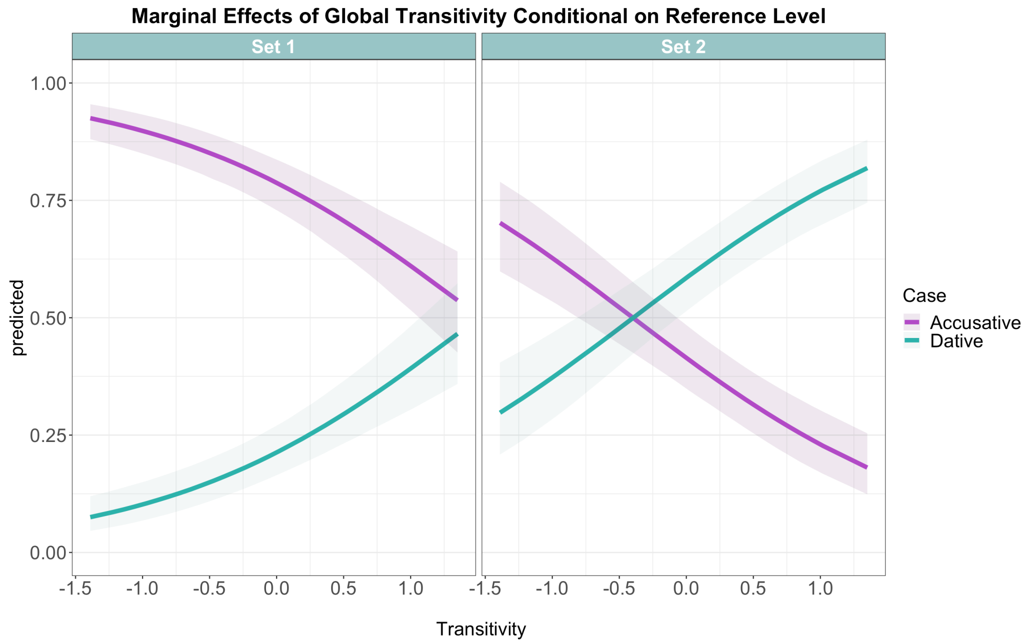

Fig 5. Marginal effects of the Transitivity score conditional on the reference level of the other predictors. For Set 1 the reference levels are PERSON: *non-3rd*, TENSE: *non-past*, CAUSATIVE: *hacer*, NUMBERSUBJ: *singular* and for Set 2 PERSON: *3rd*, TENSE: *past*, CAUSATIVE: *dejar*, NUMBERSUBJ: *plural*. The y-axis represents the posterior predicted probability for the dative clitic and x-axis the Transitivity score scaled to have standard deviation 0.5.

Predictive performance of Model-1 and Model-2

Tables 5 and 6 show the confusion matrices for Model-1 and Model-2. The predictive power of both models is examined on training and the testing data. The performance on training data tends to always be more optimistic than on testing data since the model has learned the pattern from the training data. The performance on the testing data reflects the true predictive power of the model.

The predictive accuracy on testing data is 0.78 for Model-1 and 0.68 for Model-2. Model-1, where the predictors are entered individually, achieves higher accuracy than Model-2. This is likely due to loss of information when the parameters are all collapsed into one single score as in Model-2. For example, we saw a number of interactions between the parameters in Model-1 that cannot be captured with the composite score.

Table 5. Confusion matrices for Model-1 and Model-2 on training and testing data. Shaded diagonals represent correct predictions.

Training Data						Testing Data					
Model 1			Model 2			Model 1			Model 2		
	Reference			Reference			Reference			Reference	
Prediction	Acc	Dat	Prediction	Acc	Dat	Prediction	Acc	Dat	Prediction	Acc	Dat
Acc	1579	458	Acc	1560	510	Acc	508	181	Acc	472	218
Dat	287	1118	Dat	306	1066	Dat	114	344	Dat	150	307
Accuracy:	0.78		Accuracy:	0.76		Accuracy:	0.74		Accuracy:	0.68	
95% CI:	(0.77, 0.80)		95% CI:	(0.75, 0.78)		95% CI:	(0.72, 0.77)		95% CI:	(0.65, 0.71)	
Kappa:	0.56		Kappa:	0.52		Kappa:	0.48		Kappa:	0.35	
F1:	0.75		F1:	0.72		F1:	0.7		F1:	0.63	

Model-3

In the previous models we were able to determine which parameters are relevant in the clitic case alternation, but what is the relative importance of each parameter in the alternation? Model-3 allows us to examine this via the variable importance measure. Fig 6 shows, in descending order, the most important variables of all the variables used in the study. Note that the permutation variable importance of unbiased trees in the `party` package can handle categorical variables with many levels very well [28] so COUNTRY in Model-3 represents every single country separately, which allows us to determine the effect of each variety on the clitic case.

The most important predictor is PARTICIPANTS, that is whether the infinitive verb in the causative construction is transitive or intransitive, followed by ANIMACYOBJ, CAUSATIVE, COUNTRY and AGENCYSUBJ. The five least important variables are TENSE, NUMBEROBJ, COUNT, AFFECTEDNESS and MOOD. Note that the top five variables are the same variables that had a Bayes factor larger than 1 in Model-1. For the rest of the variables we found no evidence of an effect. The exception to this is CONCRETENESS, which is relatively low in the variable importance ranking. However, this variable in Model-1 presented evidence of an effect only in the interaction with PARTICIPANTS and interactions were not entered into the random forest. We also noted that CONCRETENESS was a very sparse variable due to the low number of abstract objects in the sample and this is likely to affect its predictive power, which is what the variable importance measures.

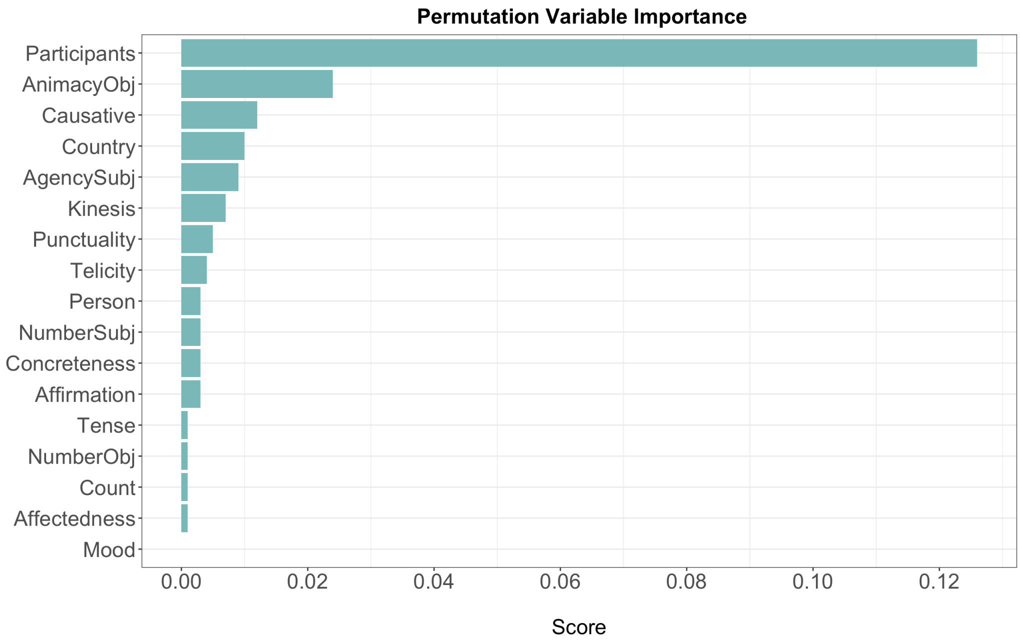

Fig 6. Permutation Variable Importance in Model-3. The x-axis represents the variable importance score.

4. Discussion

We will start off the discussion by first evaluating the hypotheses and predictions laid out in Section 1. I repeat the hypotheses below to make the discussion easier.

Hypothesis 1: The Transitivity parameters will co-vary in the same direction

Hypothesis 2: The two causative predicates will show different preferences in clitic case.

Hypothesis 3: Accusative case will align with higher Transitivity and dative case with lower Transitivity.

Hypothesis 1 is Hopper and Thompson's hypothesis where they hypothesised that the Transitivity parameters will always co-vary toward one or the other end of the Transitivity scale. To determine whether this hypothesis is borne out we need to look at the coefficient estimates of Model-1. I will limit the discussion to those parameters for which there was enough evidence of an effect, namely AGENCYSUBJ, ANIMACYOBJ, PARTICIPANTS and CONCRETENESS and their interactions. The posterior estimate coefficients for these variables are all positive except for the interaction PARTICIPANTS*CONCRETENESS, which indicates that concrete objects of transitive verbs disfavour the dative clitic. Given that these two values of the parameters are the high Transitivity values the strong version of Hypothesis 1 is not supported because they disprefer the dative clitic, which is the clitic that shows high Transitivity according to Model-2. Having said that, in Model-2 we saw that when Transitivity is operationalised as a continuous property we do see an increase in the predicted probabilities of the dative clitic. So generally speaking, the individual parameters may not all converge on the same end of the Transitivity spectrum but overall it seems that these minor divergences may disappear when all the parameters are added up. A weaker version of the hypothesis is supported because if it were the case that the parameters all differed in haphazard ways then we would not expect the results in Model-2.

With regard to Hypothesis 2, the prediction was that *hacer* would favour the dative clitic based on Enghels's previous finding [10]. In Model-1 CAUSATIVE participates in a significant interaction with AGENCYSUBJ, whose posterior mean estimate is 0.81(CI: 0.43, 1.19). The mean estimate for CAUSATIVE without the interaction is -1.18 (-1.53, -0.82) but this refers to *hacer* with non-agentive subjects and intransitive verbs. In Model-2, where no interactions were included, the posterior mean estimate is -0.35 (CI: -0.58, -0.14). Judging from Model-2, where CAUSATIVE contributes to the model on its own, Hypothesis 2 is not supported because the negative coefficient estimate means that *hacer* disfavours the dative clitic. Model-1 gives us a more nuanced interpretation and we can see that the way *hacer* behaves with respect to the clitic depends on other elements in the sentence. Thus, a categorical statement that *hacer* favours the dative clitic across the board is not supported by the data. However, we can conclude that *hacer* favours the dative clitic when its subject is agentive.

Hypothesis 3 was formulated on the basis of findings from reverse-psychological predicates where it was found that contexts higher in Transitivity corresponded to accusative marking. It should be clear by now that this is not the case in the causative construction. Model-2 clearly shows that increasing Transitivity brings about an increase in the predicted probability of the dative, not the accusative, clitic. This is an important but not an unexpected result. There are several reasons why the dative clitic is likely to be associated with higher Transitivity in this construction that may not hold in other constructions. The first thing to remember is that, in the causative construction, transitive verbs traditionally require the subject of the infinitive to be in the dative case. Although this is not categorical we saw in Model-3 that PARTICIPANTS is the most important variable. This is clearly seen in our data sample where 80% of transitive verbs co-occur with a dative clitic and 70% of intransitive verbs appear with an accusative clitic. In addition, the dative clitic in the causative construction appears to preferentially refer to animate objects. While 69% of the accusative-marked objects are animate and 31% inanimate, only 4% of dative-marked objects are inanimate and an overwhelming 96% are animate. This is probably due to extra-linguistic factors and not because of an intrinsic feature of the clitic itself because indirect objects tend to be animate, especially human. From a cross-linguistic perspective the association of dative objects and higher Transitivity is actually not uncommon. Hopper and Thompson [11] point out that what traditional grammars call *indirect objects* should be called Transitive Os (objects) instead of the traditional accusative objects because they tend to be definite and animate. Even in English, Givón [29] reports that out of 115 indirect objects in a text, 97% were definite and overwhelmingly animate and Hopper and Thompson themselves find that out of 33 indirect objects in one text, 100% were human.

The finding herein that the dative clitic is associated with higher Transitivity in Spanish causative constructions does not invalidate previous findings where the accusative clitic in reverse-psychological predicates has been found to signal high Transitivity. However, they do highlight the need to be cautious about drawing generalizations that go beyond the construction under study. General statements like "X property/morpheme signals higher Transitivity" should be avoided either so that they apply in the local domain of the study or until enough evidence has been amassed across different constructions. At least in the case of clitics, their behaviour seems to be highly structure-dependent, which limits our ability to reach the overarching generalizations that most linguists seek to make.

In terms of how well the models account for the data we saw that Model-1 achieved higher predictive accuracy on new data compared to Model-2. I noted this is likely due to the fact that the model with the continuous measure cannot capture the interactions among the Transitivity parameters so there is bound to be information loss in the conversion to the Transitivity score. Nevertheless, neither model achieves very high predictive accuracy, which indicates that while Transitivity is undoubtedly one factor determining the case of the clitic there must be other factors not included in the models that are important in the alternation. One possible variable that was not included in the models is individual variation as this type of information is not available in the corpus but it has been shown to be a significant factor in morphosyntactic variation [30], [31], [32], [33]. In addition, we must entertain the possibility that there may be idiosyncratic factors that are simply irreducible to any one variable.

As regards future research directions, in this paper, I have operationalised the Transitivity Score as 1s and 0s so that each parameter has equal chances to contribute to the total score. An alternative approach worth exploring would be to assign different weights to each parameter and see whether the predictive power of the models can improve. Moreover, like with any statistical model, we cannot guarantee that the models herein are an appropriate representation of speakers' grammars. A step to validate these findings from a psycholinguistic perspective would be to conduct psycholinguistic experiments manipulating the parameters for which we have found evidence of an effect. Only then can we be more confident that our statistical models may represent the constraints by which speakers operate.

5. Conclusion

The findings in this paper provide evidence that the alternation in clitic case in causative constructions in Spanish can be modelled using the Transitivity parameters proposed by Hopper and Thompson [11]. Model-1 showed evidence for only three of these parameters, namely AGENCYSUBJ, ANIMACYOBJ and PARTICIPANTS and their interactions. However, when Transitivity was operationalised as a continuous measure we saw that global Transitivity differentiated between the two clitics such that the dative clitic was the preferred form for high Transitivity contexts. Model-3 provided the relative importance of each parameter and PARTICIPANTS turned out to be the most important predictor. This result supports the traditional account that the dative clitic appears with transitive verbs and the accusative clitic with intransitive verbs but this is a probabilistic, not a categorical, rule.

The results that it is the dative clitic that is associated with higher transitivity and not the "usual" causative clitic also highlight the importance of limiting our conclusions to the construction under study and avoid unwarranted generalizations.

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