UID constrains the usage of topic drop in German:
experimental and corpus linguistic findings

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SFB 1102

Experimental and Corpus-based Approaches to Ellipsis (ECBAE) 2020

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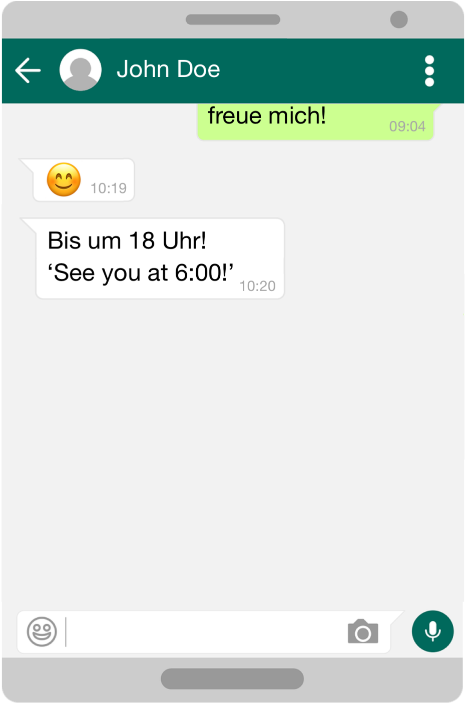
IDeaL SFB 1102

UNIVERSITÄT DES SAARLANDES


John Doe
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10:19
Bis um 18 Uhr!
'See you at 6:00!'
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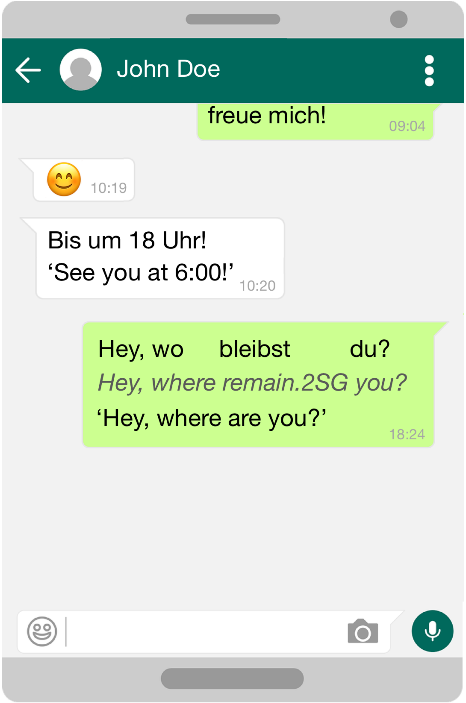
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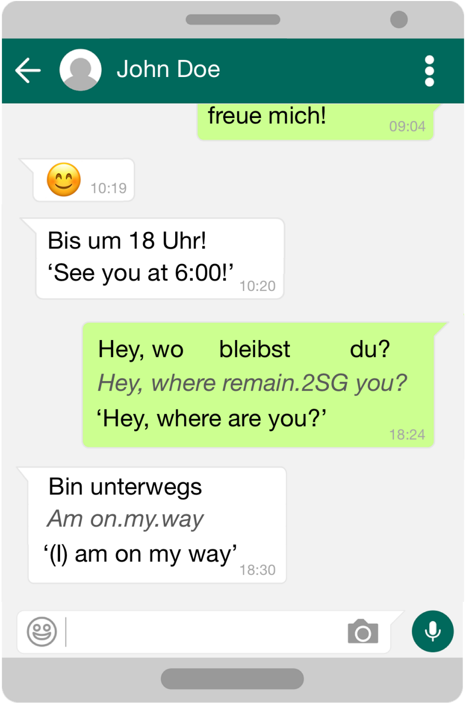
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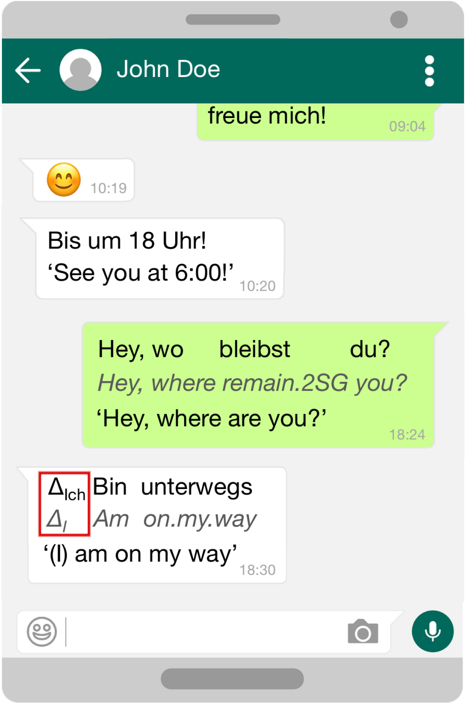
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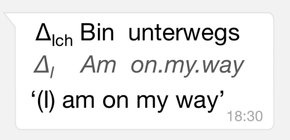
Topic drop

Topic drop in German
(Reis, 1982; Ross, 1982; Fries, 1988)

- preverbal constituent omitted from a declarative V2 sentence (1)
- sentence starts superficially with the finite verb

(1)



Outline

Research question

When do speakers **use** topic drop?

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Hypothesis

Topic drop is used when the omitted constituent is **predictable** from context and can be **easily recovered**.

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Factors according to previous literature

a) **grammatical person**: 1SG more salient (Auer, 1993; Imo, 2014)

b) **verbal inflection**: verb marked for person (Auer, 1993)

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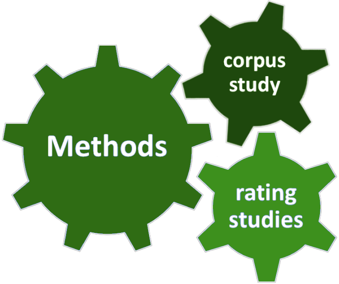

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a) **grammatical person**: 1SG more salient → *corpus, experiments*

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⇒ previous accounts based on single factor → *test factors systematically*

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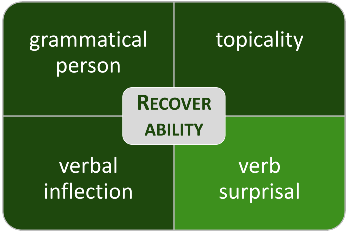
Account based on information theory

- provides an adequate **multifactorial model**
- traces back the several factors to **recoverability**
- explains additional effects of **verb surprisal**



Theoretical background

An information-theoretic account

Uniform information density (UID) hypothesis (Levy and Jaeger, 2007)

Speakers tend to distribute information / **surprisal**, defined as $-\log_2 p(word|context)$ (Shannon, 1948) and indexing processing effort (Hale, 2001), **uniformly** across utterances, not exceeding or falling below channel capacity.

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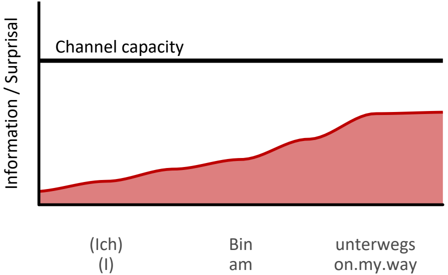

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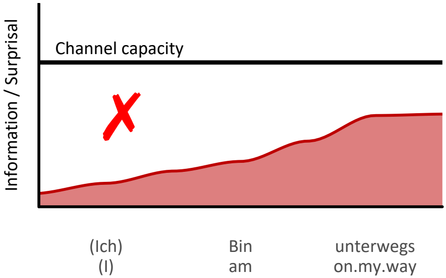

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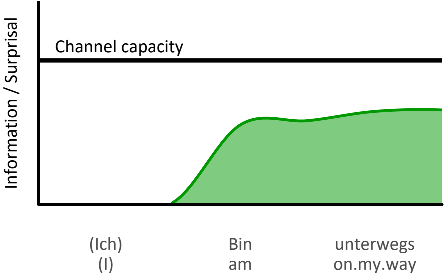

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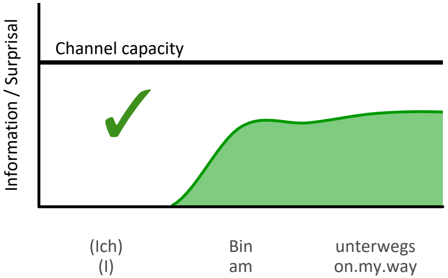

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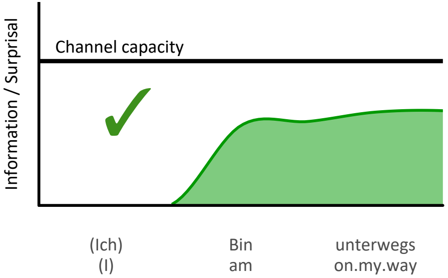

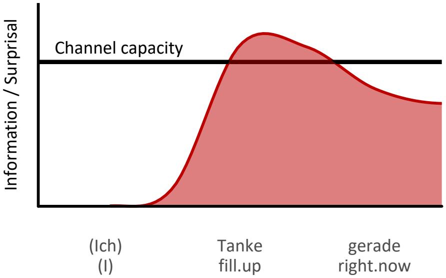

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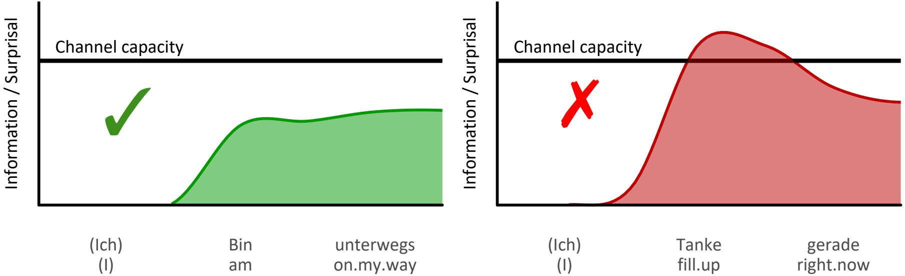

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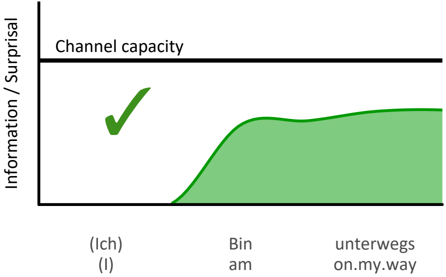

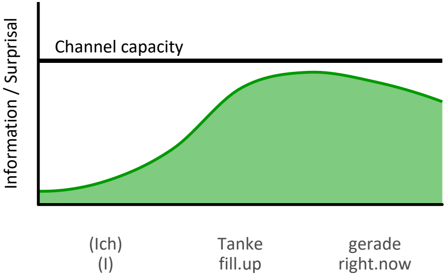

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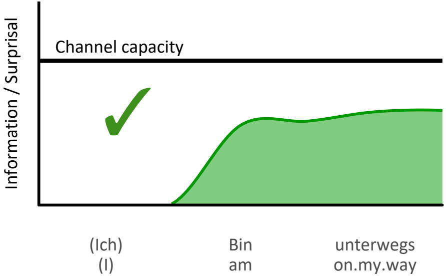

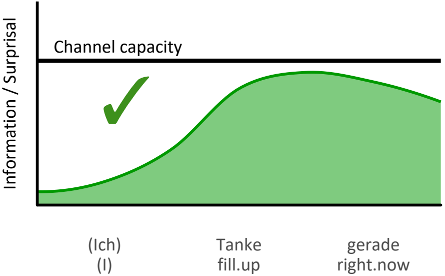

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⇒ UID account provides **unifying account** to the usage of topic drop

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- surprisal of the following verb as predictor

$\Rightarrow$ UID account provides **additional explanatory power**

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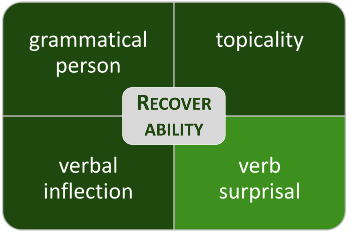

Corpus study

Corpus study – Overview

Research question

Do **grammatical person**, **verbal inflection** and **verb surprisal** influence the **frequency** of topic drop?

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Hypotheses: Topic drop is **more frequent** ...

PERSON	... with 1SG compared to 3SG
SURPRISAL	... when the initial verb is more predictable
INFLECTION	... before inflectionally marked compared to syncretic verbs

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Data set

- basis: text messages subcorpus of **FraC** fragment corpus (Horch and Reich, 2017)
- only 1SG and 3SG subjects, 290 topic drops and 162 full forms
- **verb lemma**, **verbal inflection** (explicitly marked or not), **unigram surprisal** per verb lemma from language model trained on text messages subcorpus (SRILM toolkit (Stolcke, 2002))

Corpus study – Results

Analysis

- logistic regressions in R (R Core Team, 2019)
- predict topic drop from **Person** (1SG vs. 3SG), **Surprisal** (numeric), **Inflection** (syncretic vs. marked) and all two-way interactions

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Results

Predictor	Estimate	SE	χ^2	p-value	
Person	0.64	0.12	27.63	< 0.001	***
Surprisal	–0.23	0.06	14.21	< 0.001	***
Inflection:Surprisal	0.14	0.06	4.86	< 0.05	*

Hypotheses: Topic drop is **more frequent** ...

Person ✓ ... with 1SG compared to 3SG
Surprisal ✓ ... when the initial verb is more predictable
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Corpus study – Discussion

Topic drop is **more frequent** ...

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Corpus study – Discussion

Topic drop is **more frequent** ...

PERSON ✓ ... with 1SG compared to 3SG

$\boxed{\text{1SG topic drop > 3SG topic drop}}$

- strategy to avoid surprisal minima in sentence-initial position

$\Rightarrow$ 1SG ($n = 343$) in general more frequent than 3SG ($n = 99$)

SURPRISAL ✓ ... when the initial verb is more predictable

INFLECTION ? ... before inflectionally marked compared to syncretic verbs

Corpus study – Discussion

Topic drop is **more frequent** ...

PERSON ✓ ... with 1SG compared to 3SG

SURPRISAL ✓ ... when the initial verb is more predictable

higher verb surprisal → -- topic drop

- strategy to avoid surprisal maxima in sentence-initial position

INFLECTION ? ... before inflectionally marked compared to syncretic verbs

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Topic drop is **more frequent** ...

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SURPRISAL	✓	... when the initial verb is more predictable
INFLECTION	?	... before inflectionally marked compared to syncretic verbs

$\boxed{\text{distinct inflection + higher surprisal} \rightarrow \text{++ topic drop}}$

- topic drop more likely with higher surprisal when verb is inflectionally marked

$\Rightarrow$ surprisal maximum less severe when topic drop more easily recoverable

Experiments

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Do **grammatical person**, **verbal inflection** and **topicality** influence the **acceptability** of topic drop?

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Inflection	... with 1SG **only** for inflectionally marked full verbs
Topicality	... when the omitted constituent has been set as topic before

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Experiment 1	Experiment 2
▶ tests effects of **grammatical person** and **topicality**	▶ tests effects of **grammatical person**, **topicality** and **verbal inflection**
▶ uses utterances with **inflectionally marked full verbs**	▶ uses utterances with **syncretic modal verbs**

Experiment 1

full verbs

Experiment 1 – Set-up

Acceptability rating study

- 2 × 2 × 2 design: **OMISSION** (topic drop vs. full form) × **PERSON** (1SG vs. 3SG) × **TOPICALITY** (topic continuity vs. topic shift)
- 24 items with **full verbs** like (1) + 60 fillers presented as text messaging dialogues
- 43 native speakers of German recruited from Clickworker
- rating of last utterance on 7-point Likert scale (7 = completely natural)

(1) A: 'What's new?'

a. B: Am Samstag geht Julia mit mir essen. (Sie) **lädt** mich diesmal ein.
B: On Saturday goes Julia with me eat. (She) invites_1 me this.time invites_2.

'B: On Saturday Julia dines out with me.

(She) invites me this time.' [*topic continuity* | *3SG* | *topic drop (full form)*]

Experiment 1 – Results

Analysis

- cumulative link mixed models (CLMMs) in R (Christensen, 2019)
- full model with **Omission**, **Person**, **Topicality** and all two-way interactions plus full random effects structure (Barr et al., 2013)

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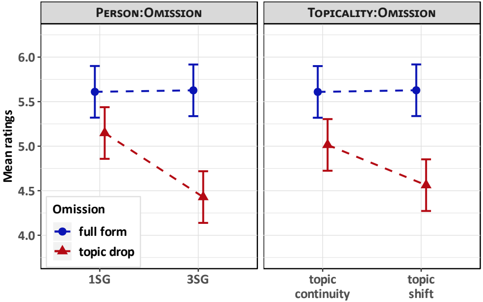

Mean ratings and 95 % CIs for experiment 1

Results

Predictor	Estimate	SE	χ^2	p-value
OMISSION	–1.45	0.38	30.74	< 0.001 ***
PERSON:OMISSION	1.13	0.25	20.74	< 0.001 ***
TOPICALITY:OMISSION	0.69	0.25	7.97	< 0.01 **

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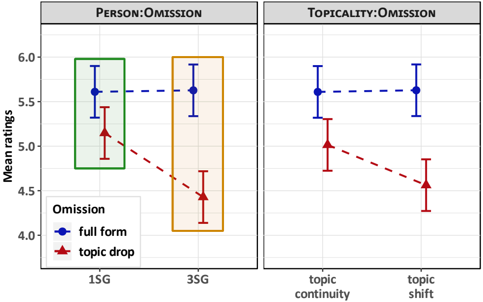

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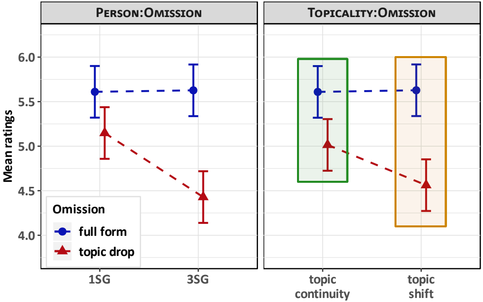

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Topic drop is **more acceptable** ...

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Topic drop is **more acceptable** ...

PERSON ✓ ... with 1SG compared to 3SG

1SG topic drop > 3SG topic drop

- 1SG topic drop **more frequent** (see corpus study) and **more acceptable**
  $\Rightarrow$ in line with **UID** account and previous literature

TOPICALITY ✓ ... when the omitted constituent has been set as topic before

Experiment 1 – Discussion

Topic drop is **more acceptable** ...

PERSON ✓ ... with 1SG compared to 3SG

TOPICALITY ✓ ... when the omitted constituent has been set as topic before

topic continuity $\rightarrow$ ++ topic drop

- in line with **UID** account
  $\Rightarrow$ topic **more predictable** $\Rightarrow$ **lower surprisal** $\Rightarrow$ topic drop **more acceptable**

Experiment 2

modal verbs

Experiment 2 – Set-up

Acceptability rating study

- 2 × 2 × 2 design: **OMISSION** (topic drop vs. full form) × **PERSON** (1SG vs. 3SG) × **TOPICALITY** (topic continuity vs. topic shift)
- 24 items with **modal verbs** **??** + 60 fillers presented as text messaging dialogues
- 48 native speakers of German recruited from Clickworker
- rating of last utterance on 7-point Likert scale (7 = completely natural)

Experiment 1

(2)	(Sie)	**lädt**	mich	ein.
	(She)	invites_1	me	invites_2

(3)	(Ich)	**lade**	sie	ein.
	(I)	invite_1	her	invite_2

Experiment 2

(4)	(Sie)	**möchte**	mich	einladen.
	(She)	wants	me	invite

(5)	(Ich)	**möchte**	sie	einladen.
	(I)	want	her	invite

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- 24 items with **modal verbs** **??** + 60 fillers presented as text messaging dialogues
- 48 native speakers of German recruited from Clickworker
- rating of last utterance on 7-point Likert scale (7 = completely natural)

Experiment 1

(2) (Sie) **lädt** mich ein.
(She) invites_1 me invites_2

(3) (Ich) **lade** sie ein.
(I) invite_1 her invite_2

Experiment 2

(4) (Sie) **möchte** mich einladen.
(She) wants me invite

(5) (Ich) **möchte** sie einladen.
(I) want her invite

Experiment 2 – Results

Analysis

- cumulative link mixed models (CLMMs) in R (Christensen, 2019)
- full model with **Omission**, **Person**, **Topicality** and all two-way interactions plus full random effects structure (Barr et al., 2013)

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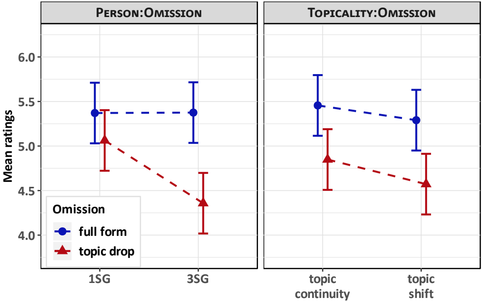

Mean ratings and 95 % CIs for experiment 2

Results

Predictor	Estimate	SE	χ^2	p-value	
OMISSION	–0.63	0.25	21.22	< 0.001	***
PERSON:OMISSION	–1.02	0.24	18.72	< 0.001	***
TOPICALITY:OMISSION	0.32	0.23	1.82	0.18	

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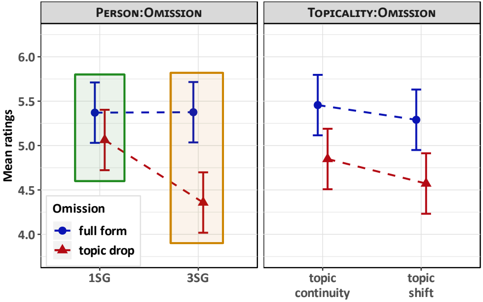

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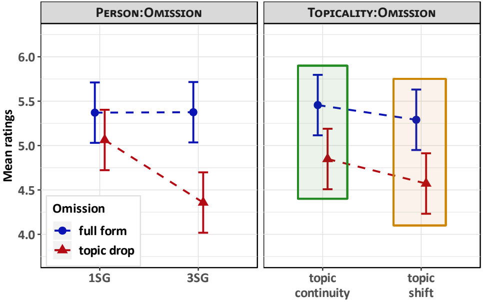

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Experiment 2 – Discussion

Topic drop is **more acceptable** ...

PERSON	✓	... with 1SG compared to 3SG
INFLECTION	✗	... with 1SG **only** for inflectionally marked full verbs
TOPICALITY	✗	... when the omitted constituent has been set as topic before

Experiment 2 – Discussion

Topic drop is **more acceptable** ...

PERSON ✓ ... with 1SG compared to 3SG

INFLECTION ✗ ... with 1SG **only** for inflectionally marked full verbs

$\boxed{\text{1SG topic drop > 3SG topic drop}}$

- 1SG topic drop **more acceptable** even for syncretic modal verbs
  $\Rightarrow$ preference for topic drop of 1SG does not hinge on distinct verbal inflection

TOPICALITY ✗ ... when the omitted constituent has been set as topic before

Experiment 2 – Discussion

Topic drop is **more acceptable** ...

PERSON	✓	... with 1SG compared to 3SG
INFLECTION	✗	... with 1SG **only** for inflectionally marked full verbs
TOPICALITY	✗	... when the omitted constituent has been set as topic before

topic continuity **+ distinct inflection** $\rightarrow$ ++ topic drop

- unexpected given exp. 1
  - $\Rightarrow$ **combination** of topicality and distinct verbal inflection in exp. 1
  - $\Rightarrow$ topic continuity alone in exp. 2 **not enough** to facilitate recoverability

General discussion

Summary

Factor	Observation	Corpus	Experiments
PERSON	1SG topic drop > 3SG topic drop	✓	✓
INFLECTION	distinct inflection + higher surprisal / topic continuity $\rightarrow$ ++ topic drop	✓	✓
SURPRISAL	higher verb surprisal $\rightarrow$ -- topic drop	✓	–
TOPICALITY	topic continuity + distinct inflection $\rightarrow$ ++ topic drop	–	✓

Support for an **information-theoretic account** to **topic drop**

$\Rightarrow$ **UID provides unifying explanation to usage of topic drop**

$\Rightarrow$ **interaction of several factors facilitates recovering the omitted constituent**

$\Rightarrow$ **additional explanatory power through accounting for effects of verb surprisal**

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