Show or Tell? Exploring when (and why) teaching with language outperforms demonstration

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Abstract

People use a wide range of communicative acts across different modalities, from concrete demonstrations to abstract language. While these modalities are typically studied independently, we take a comparative approach and ask *when* and *why* one modality might outperform another. We present a series of real-time, multi-player experiments asking participants to teach concepts using either demonstrations or language. Our first experiment ($N = 416$) asks *when* language might outperform demonstration. We manipulate the *complexity* of the concept being taught and find that language communicates complex concepts more effectively than demonstration. We then ask *why* language succeeds in this setting. We hypothesized that language allowed teachers to reference *abstract* object features (e.g., shapes and colors), while demonstration teachers could only provide concrete examples (specific positive or negative objects). To test this, our second experiment ($N = 568$) ablated object features from the teacher’s interface. This manipulation severely impaired linguistic (but not demonstrative) teaching. Our findings suggest that language communicates complex concepts by directly transmitting abstract rules. In contrast, demonstrations transmit examples, requiring the learner to infer the rules.

Keywords: pedagogy, communication, language, demonstration, abstraction

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1. Introduction

Human teaching takes many forms. For instance, imagine teaching a friend how to play chess and trying to convey *how rooks move*. You could *demonstrate* the rule by dragging a rook along a row, then a column. Alternatively, you could
5 *describe* the rule with language, saying “Rooks move along rows and columns” without ever touching a piece. These distinct modalities both play a role in human pedagogy—but what are their strengths, and how do they work? When and why is language more effective than demonstration?

Researchers have taken different approaches to this question. Classic work
10 has provided rich qualitative insights into natural settings (Scribner & Cole, 1973; Carroll & Bandura, 1990; Chi, 2013). For example, younger children tend to teach via nonverbal demonstration, while older children and adults tend to use language (Ellis & Rogoff, 1982; Strauss et al., 2002). Meanwhile, more tightly controlled experiments have tested quantitative predictions from computational
15 theories (e.g. Shafto et al., 2014), providing mechanistic insight into specific behaviors such as demonstration (Gweon et al., 2010; Buchsbaum et al., 2011; Ho et al., in press), verbal explanation (Chopra et al., 2019), or evaluative feedback (Ho et al., 2019). Yet this work has largely focused on *individual* teaching modalities without considering relationships between them (but see
20 Tessler et al., 2020). This paper seeks a middle ground, introducing a novel interactive teaching paradigm to directly compare modalities while controlling for factors that may mediate their efficacy.

We report a pair of studies that compare two communication modalities—*demonstration* and *language*. Demonstration (*showing* someone how chess pieces
25 move) is a form of example-based teaching (Bandura, 1965; Csibra & Gergely, 2009; Shneidman et al., 2016). Demonstrations are non-symbolic communicative acts, relying on shared understanding of a problem domain (such as physical affordances and goals, Gergely & Csibra, 2003; Gergely & Jacob, 2012). The capacity to generate and understand demonstrations is foundational, emerging
30 early in childhood (Butler & Markman, 2012; Király et al., 2013; Gweon

et al., 2010; Gweon & Schulz, 2018; Leonard et al., 2017). Language (e.g., *telling* someone the rules of chess) is another cognitively privileged mechanism for transmitting knowledge (Grice, 1975). Language relies on shared conventions (Clark, 1996) to convey information about categories (Gelman & Markman, 1986, 1987), relations (Rattermann & Gentner, 1998; Loewenstein & Gentner, 2005), and causal structures (Lombrozo, 2006; Tessler & Goodman, 2019). While both are fundamental means of knowledge transmission, they operate by different mechanisms: language uses conventionalized forms of reference to transmit abstract information, while demonstrations instantiate that information in concrete examples (Csibra & Shamsudheen, 2015).

But *when* and *why* might one be preferred? We develop a pair of concept-teaching studies to address these questions. Experiment 1 asks *when* language outperforms demonstration, varying the teaching *content* by manipulating the concept complexity (Shepard et al., 1961; Feldman, 2000). We find that concept complexity has systematic and differential effects on these modalities: language outperforms demonstration when communicating complex concepts. We then ask *why*, hypothesizing that language succeeds by encoding the abstract, underlying rule (Lombrozo, 2006). Experiment 2 tests this by varying the teaching *context*: we ablate the teacher’s view of object features, while leaving spatial context intact. This forces teachers to communicate about specific objects rather than object features, which severely impairs linguistic teaching while leaving demonstrative teaching unaffected. This systematic comparison supports the idea that language relies on shared abstractions to efficiently transmit complex concepts. In contrast, demonstrations struggle to communicate such concepts, but are less reliant on shared abstractions.

2. Experiment 1: Language conveys complex concepts better than demonstration

Concepts can be more or less complex. Intuitively, the rule for *how rooks move* is simpler than the rule for *castling*.¹ Increasing complexity makes individual learning more difficult (Shepard et al., 1961; Feldman, 2000) and favors abstract problem representations (Koedinger et al., 2008). We thus predicted that both modalities would suffice for teaching simple concepts, but language could better convey complex ones. To test this, we introduce a collaborative teaching game that places pairs of participants in an interactive virtual environment. The environment contains colored shapes with different point values. One participant, the *teacher*, can see the objects’ values but is unable to act in the environment. Consequently, they must communicate this information to their partner, the *learner*, who controls an avatar in the environment. We manipulated the communication modality and concept complexity in a fully between-subjects design. In the *language* condition, teachers sent chat messages to the learner; in the *demonstration* condition, teachers produced movement trajectories instead (see Fig. 1). Finally, we manipulated complexity by changing the mapping of point values to object visual features, giving rise to different underlying concepts.²

2.1. Methods

2.1.1. Participants

We recruited 480 participants using Prolific (www.prolific.co). Participants were required to be fluent in English, possess an approval rating of 95%, and be located within the United States, United Kingdom, or Ireland. They

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¹“A king can be moved two spaces towards a rook, and the rook to the opposite side of the king, *if* the king is not in check, neither piece has previously moved, there are no pieces between them, and the king does not pass through a square that would place it in check.”

²The study was approved by the Princeton IRB; our sample size and planned analyses were pre-registered at https://aspredicted.org/S8S_FMQ. Code and data are available at <https://github.com/tsumers/show-or-tell>.

Figure 1: *Experimental paradigm and conditions.* A: Each trial began with an action phase, in which the learner was placed in a new level and collected objects according to their beliefs about which were positive. Learners generally began the task choosing randomly (trial 1 score: $M=-.09$, $SD=2.23$). B: After the action phase, teachers communicated via demonstration or language. Over the course of the experiment (10 trials), teachers were generally able to communicate the concept (trial 10 score: $M=3.30$, $SD=2.65$), although this varied substantially by condition (Table S1). C: Manipulating concept complexity. Positive and negative objects were “masked” by Boolean concepts of varying complexity.

80 were paid \$2.25 with a score-based bonus up to \$1.75. We excluded seven participants who accidentally re-started the experiment after refreshing their browser, for a final sample of 227 pairs, 208 of whom completed all 10 levels.

2.1.2. Procedure

After reading instructions, all participants completed two practice trials to familiarize them with the environment. Participants were then paired, assigned
85 teacher or learner roles, and played a practice trial together. They then played 10 trials of a communication task. Each trial proceeded as follows. First, in the action phase (Fig. 1A), the learner was given 30 seconds to study the level and plan their movements. They then had 8 seconds to move the avatar to collect
90 objects while the teacher watched. The learner was only shown the shapes and colors, but the teacher could also see the underlying values. After 8 seconds,

the action phase ended and both players were shown the net score.³ They then proceeded to a teaching phase (Fig. 1B). *Language* teachers were allowed message their partner through a one-way chat interface; *demonstration* teachers
95 re-played the level while the learner watched. After 10 trials, both players completed an exit survey, which included a measure of concept knowledge: learners were asked the value of each of the 8 possible objects (+1/-1/“Don’t Know”).

2.1.3. Stimuli

The player began each trial in the center of the screen, with a cluster of five
100 objects in each corner. Each object was assigned a positive (+1) or negative (-1) value and a set of visual features according to different Boolean concepts (Fig. 1C). We used three features, each taking two possible values, for a total of $2^3 = 8$ feature combinations (color: blue or pink; shape: square or triangle; fill: solid or hollow). We assigned features using three levels of complexity
105 — *low*, *intermediate*, and *high*, corresponding to Shepard concepts I, II, and III (Shepard et al., 1961) or Boolean complexity 1, 4, and 6, in the taxonomy of Feldman (2000). Within each complexity condition, we randomized features to mitigate salience biases.⁴ To allow direct comparison of movement trajectories, values of objects in each location were generated randomly but fixed across
110 participants for each trial. Thus all participants proceeded through the same set of 10 randomly generated maps, but with different visual features assigned to locations.

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³For example, collecting three objects with a value of +1 and one with a value of -1 would yield a net score of 2.

⁴For example, in the *low* complexity condition, a single dimension determined the value. Pairs could be assigned blue as positive (pink as negative), pink as positive (blue as negative), squares as positive (triangles as negative), and so on.

Figure 2: *Experiment 1 results*. A: linguistic teaching sustained higher transmission fidelity as concept complexity increased. B: learners tended to simplify the concept being taught, inferring a lower-complexity concept. This was particularly pronounced for demonstration learners. Error bars show 95% CI.

2.2. Results

2.2.1. Transmission Fidelity

Our primary hypothesis concerned transmission fidelity. We expected that linguistic teachers could convey the underlying concept more effectively than demonstrative teachers, especially for more complex concepts. We operationalized transmission fidelity using *learner concept accuracy*, the number of correct responses in the exit survey (Fig. 2A). To test our hypothesis, we used a binomial logistic regression predicting the number of correct responses (out of 8). We included predictors for communication modality, (Boolean) concept complexity, and their interaction. To interpret main effects, we centered the regressors.⁵ Language afforded significantly higher transmission fidelity than demonstration ($\beta = .38$, $t(202) = 6.66$, $p < .0001$). As complexity increased, fidelity in both decreased ($\beta = -.29$, $t(202) = -9.98$, $p < .0001$). However, we also found a

⁵We treated complexity as a continuous variable and subtracted the mean, $(1 + 4 + 6) / 3$. We sum coded the communication condition (*language* = 1, *demonstration* = -1).

significant interaction. On more complex concepts, demonstration fared significantly worse than language ($\beta = .11$, $t(202) = 3.74$, $p < .001$; see Table S2). Task performance followed a similar pattern (see Appendix A).

2.2.2. Concept Simplification

130 Our analysis of transmission fidelity asked *how much* concept knowledge learners acquired. We now investigate *what* they learned. Rather than make random errors, we hypothesized that demonstration learners would formulate a simpler rule based on fewer features (Goodman et al., 2008), thereby reducing its complexity. For example, a demonstration learner assigned the most complex
 135 concept in Fig. 1C (Boolean complexity 6) might observe their teacher collect mostly triangles and infer that all and only triangles were positive (Boolean complexity 1). To operationalize this, we compared the Boolean complexity of the learner’s survey responses to the true concept (Fig. 2B). We ran a regression analysis predicting the complexity of the learner’s inferred concept as
 140 a function of the communication modality (contrast-coded as before), controlling for true complexity (dummy-coded with *low* as the baseline). We found a weak effect of modality ($\beta = .24$, $t(202) = 2.01$, $p = .045$; see Table S4 for full model). While all teachers struggled to convey the most complex concepts, demonstration learners simplified even intermediate ones.

145 2.3. Discussion

As predicted, linguistic teaching outperformed demonstration at transmitting complex concepts. Demonstration learners tended to prefer simple explanatory rules; in contrast, language allowed teachers to more precisely specify complex feature combinations. Of course, factors aside from modality may inhibit
 150 learning of more complex concepts. For example, teachers may have deliberately simplified harder concepts, teaching “good enough” rules intended to maximize the learner score rather than transmit the full concept (see Table S6 for an example of teaching a simplified concept first). Learning may also be affected by more general factors such as memory and attention. However, because these

155 factors were held constant across conditions, our results reflect modality-based differences for the communicative pair as a whole.

These findings suggest language matches or outperforms demonstration regardless of concept complexity. But what allows language to transmit complex concepts? Developmental studies suggest that language aids learning by encoding *task-relevant abstractions* (Rattermann & Gentner, 1998; Loewenstein & Gentner, 2005). Our second experiment hypothesized that without such abstractions, language—but not demonstrations—would be severely impaired.

3. Experiment 2: Linguistic (but not demonstrative) teaching relies on shared abstractions

165 Experiment 1 found that language outperforms demonstration at communicating complex concepts. Why might this be the case?

Consider the statement “Rooks move along rows and columns.” *Rook* is an *abstraction*: it refers to a *set* of objects defined by the label *rook* (Gelman & Markman, 1986; Gelman, 2004). But what if one did not have such a label? One could imagine referring to *specific* rooks: “*That piece in the corner* moves along rows and columns.” But this creates ambiguity: how should the listener generalize? Does the same property extend to the opponent’s identically-shaped (but differently colored) pieces? Intuitively, this seems cumbersome. Indeed, in Experiment 1, most language teachers expressed rules by referring to abstract object *features*: “filled pink shapes and hollow blue shapes” (Fig. 1B), rather than specific objects. In contrast, demonstrations *cannot* refer to abstract features: physical actions necessarily engage with physical objects.

This motivates our hypothesis: such *shared abstractions* underpin language’s success in Experiment 1. To test this, we introduced a new manipulation: we removed the abstract object features (shape, color, and fill) from the teacher’s interface. Teachers in the “Locations and Features” condition had the same interface as Experiment 1, while teachers in the “Locations Only” condition could only see objects’ values (Fig. 3A). Such teachers knew which objects were

positive or negative but could not refer to their abstract features. We hypothe-
sized this would impair linguistic teaching while leaving demonstrative teaching
largely unaffected.⁶

3.1. Methods

3.1.1. Participants

We recruited a (pre-registered) sample of 640 participants on Prolific using
the same qualifications and payment as Experiment 1. Thirteen were excluded
after accidentally refreshing their browser and re-starting the task. Our final
sample contained 298 pairs, of whom 284 completed all 10 levels.

3.1.2. Materials and procedure

We again used a between-subjects design crossing modality (*language* vs.
demonstration) with complexity (*low* vs. *intermediate*; the hardest concept
level was removed). To manipulate teachers' ability to use abstractions, we in-
troduced a third condition, shared context (*features and locations* vs. *locations*
only). *Features and locations* teachers were given the same user interface as Ex-
periment 1. *Locations only* teachers were given an ablated interface: they saw
the value objects, but *not* their features (shape, color, and fill; Fig 3A). Other-
wise, the procedure was the same as Experiment 1, using the same sequence of
10 trials.

3.2. Results

3.2.1. Transmission Fidelity

As in Experiment 1, our primary variable of interest was the learner's con-
cept knowledge (Fig. 4A). We hypothesized *locations only* context would neg-
atively affect linguistic teaching, without impairing demonstration. To test
for an interaction between communication modality and context, we again
used a binomial logistic regression predicting correct responses on the learner's

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⁶Our pre-registration is available at https://aspredicted.org/ZHS_YW1

Figure 3: *Manipulating access to abstractions in Experiment 2.* A: Under the *locations only* condition, teachers could not see object features. They could only see *which* objects were positive. B/C: *Locations only* affected linguistic teaching, but not demonstrations. Top: demonstration trajectories from the second level. Teachers in both conditions relied on score-maximizing demonstrations; here, they overwhelmingly collected the five positive objects in the bottom right, then moved as far as possible towards the top right, which was the next best corner. Bottom: most common words in each condition. Linguistic teachers in the two conditions used very different strategies: *Locations and features* teachers relied primarily on the features (shape, color, and fill), while *Locations only* teachers relied on behavioral (“first 3 positive”) or spatial (“top left the top 2 are negative”) references to describe which objects were positive.

Figure 4: *Experiment 2 results*. A: All modalities succeeded at communicating low complexity concepts. However, increased complexity severely impairs transmission fidelity for all *demonstrations* and *locations only* linguistic teachers—while leaving linguistic teachers with access to abstract features largely unaffected. B: Cumulative scores reveal that *location-only* linguistic teaching lagged behind other conditions (see Figure S4 for per-level scores). Error bars show 95% CI.

210 exit survey. Predictors included complexity, communication modality, context (all effect-coded), and the communication-context interaction. All four terms were significant, critically including the context-communication interaction ($\beta = .34, t(279) = 6.90, p < .001$; see Table S9), consistent with our hypothesis that *locations only* context would impair linguistic teaching more
 215 than demonstration.

3.2.2. Cumulative Scores

Task performance may provide another perspective on communicative success: did different teaching modalities allow learners to reach higher scores? Specifically, we examine the *cumulative score* (Fig. 4B). If two learners end
 220 the experiment with equal concept knowledge but different scores, this implies that the higher-scoring learner acquired the concept *faster*. We used a linear regression to predict each learner’s cumulative score using same predic-

tors as above.⁷ The results suggest even more extreme limitations of *locations only* context linguistic teaching. Even in the *low* complexity condition, these
 225 pairs scored worse than pairs in either *demonstration* condition (interaction $\beta = 4.13, t(279) = 5.58, p < .001$, see Fig. S4 and Table S10 for full model).

3.2.3. Teacher Strategies and Subjective Difficulty

How did removing object features affect teaching? Language teachers in different context conditions used very different words (Fig. 3B/C; Appendix C).
 230 *Features and locations* teachers relied heavily on the abstract features (color, shape, and fill), while *locations only* teachers primarily referenced specific positive objects (e.g., using spatial references).

In contrast, demonstration teachers were largely unaffected by context. Teachers' most common strategy was to maximize their score: 75% (1078 of 1430) of
 235 demonstrations achieved the highest possible points per level. There was not a significant difference in teachers' rates of score-maximizing demonstrations across the four conditions ($F(3, 139) = 1.515, p = .213$). In other words, most demonstration teachers taught by acting optimally—a viable strategy even when the teacher and learner have differing representations of the environment.

Finally, we explored the division of labor across conditions and roles by
 240 asking participants to rate how difficult the game was (Fig. 5). Participants generally found the *low* complexity condition easy. However, at *intermediate* complexity, theoretically interesting differences emerged across conditions and roles ($F(7, 278) = 18.76, p < .0001$; see Table S21 for Tukey HSD tests).
 245 *Language* teachers and learners agreed that sharing *features and locations* was easier than *locations only*. Both roles thought *features and locations* was easy; both thought *locations only* was hard. In contrast, in *demonstration* conditions, *learners* found the task more difficult than *teachers*; the shared *context* did not matter. This asymmetry suggests that demonstrative teaching places the cognitive
 250 burden on the learner: it was easy for teachers to provide demonstrations,

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⁷This model was a simplification of our pre-registered analysis; see Appendix E for details.

but difficult for learners to infer the underlying concept.

3.3. Discussion

Our findings support the hypothesis that language succeeded in Experiment 1 by relying on shared *abstractions*: allowing reference to object *features* rather than the objects themselves. Lacking access to these features, linguistic teaching suffered while demonstrations did not. We note that even with *locations only*, linguistic teachers were in principle capable of communicating more information than demonstrative teachers. Indeed, one *locations only* language teacher specified the value of every object in every trial (Table S18). In general, however, such strategies were difficult and inefficient: despite sending more text (Fig. S2), *locations only* teachers struggled to transmit the concept.⁸

4. General Discussion

Teaching is central to human social life and has been examined extensively from evolutionary (Tomasello, 2009), developmental (Csibra & Gergely, 2009), cross-cultural (Shneidman et al., 2016) and computational (Shafto et al., 2014) perspectives. Yet recent experimental work has largely studied single modalities without considering their relative efficacy. Our study compared different modalities in a rich but controlled communication task.

In our experiments, *language* teachers excelled at communicating abstract information. However, without access to object features, they found it challenging to communicate the same information in terms of specific objects. In contrast, *demonstration* teachers struggled to communicate complex concepts,

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⁸We note two possible concerns regarding *locations only* linguistic teaching. First, the condition may have been difficult for teachers to understand. Examination of chat logs revealed several teachers who either failed to understand how the learner’s perspective differed from theirs or offered encouragement rather than teaching. Removing these pairs, however, did not affect our results (Appendix D). Second, the lack of spatial structure made referencing specific objects particularly challenging. However, a followup study with more spatial structure replicated our findings (Appendix F).

Figure 5: *Participants' self-reported difficulty ratings.* F = features, L = Locations. Participants in the *low* complexity condition generally found the experiment easy. However, significant differences emerged in the *intermediate* complexity condition. In the language conditions, difficulty varied by *context*: teachers and learners agreed that the *features and locations* condition was easy and the *locations only* condition was hard. In the demonstration conditions, difficulty varied by *role*: teachers thought the task was easy, while learners thought the task was hard. Error bars show 95% CI.

but were largely unaffected by removing object features. This pattern highlights a key difference between modalities: language may use *abstract* labels to convey
 275 *abstract* information, whereas demonstrations use *concrete* examples, forcing the learner to *infer* abstract information (Hume, 1748; Butler & Markman, 2016). While humans possess a remarkable ability to learn from such data (Baldwin et al., 1993; Butler & Markman, 2012; Gergely et al., 2007; Csibra & Gergely, 2009; Shafto et al., 2014), a conventionalized lexicon allows language to directly
 280 encode abstract information (Csibra & Shamsudheen, 2015; Gelman & Markman, 1986). Notably, while learning from expert demonstrations is a historically popular approach in robotics (Abbeel & Ng, 2004; Argall et al., 2009), recent trends in the field emphasize learning from language instead (Luketina et al., 2019; Tellex et al., 2020).

285 However, the present study captures only a small slice of human communication. We enforced one-way communication, hindering discourse repairs (Dingemanse et al., 2015) and *ad-hoc* formation of new linguistic abstractions (McCarthy et al., 2021) or signaling conventions (Galantucci & Garrod, 2011; Scott-Phillips et al., 2009). In addition, we studied transmission of a particular kind
 290 of information: Boolean concepts (Shepard et al., 1961). Tradeoffs between modalities may differ when teaching other types of concepts (e.g. fundamentally physical athletic concepts, Martens, 1975). Indeed, despite extensive specialized vocabularies, demonstrative teaching is widespread in domains such as music (Dickey, 1991; Weeks, 1996), dance (Keevallik, 2010), cooking (Mondada,
 295 2014), sports (Evans & Reynolds, 2016), martial arts (Răman, 2019), medical procedures (Svensson et al., 2009) and vocational training (Asplund & Kilbrink, 2018). Finally, we studied modalities independently; naturalistic teaching may interleave them, such as narrating a demonstration (Carroll & Bandura, 1990) to establish shared linguistic abstractions.

300 Our findings suggest several avenues of future work. First, our experimental paradigm may support extending computational models to interactive multi-modal teaching. Communication is classically viewed as a means to intervene on abstract beliefs (Grice, 1975; Goodman & Frank, 2016; Shafto et al., 2021), but it

is inherently grounded in real-world actions: humans necessarily infer partners’
305 beliefs through observations (Baker et al., 2017) and integrate information from
different modalities (Carroll & Bandura, 1990; Davis-Unger & Carlson, 2008;
Butler & Tomasello, 2016). Thus, models of communication situated within
decision-making environments (Bridgers et al., 2019; Fisac et al., 2020; Sumers
et al., 2021) could begin to explain interactive, multi-modal communicative acts.

310 Finally, transmission fidelity is central to accounts of cumulative cultural
evolution (Tomasello, 2009; Lewis & Laland, 2012), but the question of which
modalities are necessary or sufficient to accumulate knowledge remains open.
Empirical work has used tasks such as stone tool making (Morgan et al., 2015;
Lombao et al., 2017) or complex problem solving (Dean et al., 2012; Tessler et al.,
315 2021; Thompson et al., 2022), but measuring knowledge accumulation in these
domains is challenging. In contrast, Boolean concepts allow us to precisely track
what individuals learned.⁹ Future work could extend our paradigm to iterated
settings to directly measure the acquisition and refinement of complex concepts
over multiple generations.

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⁹For example, Lombao et al. (2017) use observed behaviors (coded sequences of actions)
and task outcomes (the quality and quantity of stone flakes produced) to compare teaching
modalities. They then suggest that language succeeds due to better communication of specific
conceptual knowledge (e.g. the idea of a “percussion platform”). Our paradigm allows us to
query the learner for their precise concept knowledge, providing direct evidence for effects
such as concept simplification (Experiment 1, Fig. 2B).

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Supplemental Materials for Show or Tell? Exploring when (and why) teaching with language outperforms demonstration

Theodore R. Sumers, Mark K. Ho, Robert D. Hawkins, Thomas L. Griffiths

This document contains model details and supporting analyses. Code and data can be found at <https://github.com/tsumers/show-or-tell>.

Appendix A: Experiment 1

This section contains full results, model details, and additional analysis for Experiment 1 (Section 2 in the main paper).

Complexity	Communication	N	Accuracy		Cumulative Score		Inferred Complexity	
			Mean	SD	Mean	SD	Mean	SD
Low	Language	29	.84	.32	30.3	10.5	1.0	.63
	Demonstration	36	.86	.25	27.9	12.4	1.2	.61
Intermediate	Language	35	.73	.36	19.8	13.4	3.5	1.6
	Demonstration	37	.43	.37	6.5	13.0	2.5	2.0
High	Language	39	.67	.33	18.5	13.0	3.7	2.1
	Demonstration	32	.45	.27	10.8	8.6	3.2	2.1

Table S1: Summary of results for Experiment 1.

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	0.73	0.06	12.87	< 2e-16
Communication	0.38	0.06	6.66	2.76e-11
Boolean Complexity	-0.29	0.03	-9.98	< 2e-16
Comm : Complexity	0.11	0.03	3.74	0.000182

Table S2: Experiment 1 transmission fidelity (Section 2.2.1). Following Feldman (2000), we treated each concept’s Boolean complexity as a continuous variable (Low = 1, Intermediate = 4, High = 6) and centered it by subtracting off the mean $(1+4+6)/3$. A nested model comparison confirmed that adding the interaction effect significantly improved the model ($\chi^2(1) = 13.90, p < .001$).

Task Performance: Cumulative Score

See main text, Section 3.2.2 for a discussion of cumulative score as a measure for transmission fidelity. Our intent was to use scores to disambiguate learning rates within conditions that ended with equal concept knowledge. However, in Experiment 1, scores broadly followed transmission fidelity (see Fig. S1) and thus did not afford further disambiguation of conditions; instead, it corroborates concept knowledge results. We include tests here for completeness.

We used a linear regression to predict each learner’s cumulative score using the concept complexity (dummy-coded with *low* as the default) and teaching modality (contrast-coded as before). This was a simplification of our pre-registered exploratory analysis; see Appendix E for details including Fig. S3 for learning curves. Scores were significantly lower for *intermediate* and *high* complexity than *low* complexity, but there was no main effect of communication. The communication-complexity interaction at the *intermediate* level was significant ($\beta = 5.42, t(200) = 2.62, p < .01$), while the interaction at the *high* level was not; see Table S3 for the full regression results. This broadly mirrors our findings for transmission fidelity. We hypothesize that the lack of a significant difference in the *high* complexity condition reflects difficulty *using* a more complex concept to select the best subset of objects. To confirm that the two were in fact related, we used a linear regression to predict the learner’s score from their concept knowledge, finding a significant correlation ($\beta = 26.98, t(204) = 160.2, p < .0001$); see Table S5.

Figure S1: Cumulative scores over the course of the experiment. These generally followed a similar pattern to transmission fidelity (Fig. 2, main paper).

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	29.07	1.51	19.31	< 2e-16
Communication	1.21	1.51	0.80	0.42358
Intermediate Complexity	-15.93	2.07	-7.69	6.62e-13
High Complexity	-14.43	2.10	-6.88	7.52e-11
Int. Complexity : Comm	5.42	2.07	2.62	0.00955
High Complexity : Comm	2.66	2.10	1.27	0.20699

Table S3: Experiment 1 cumulative scores. Unlike concept knowledge, learner scores were nonlinear in complexity. We re-coded complexity as a categorical variable (Low as default). A nested model comparison confirmed that adding the interaction effects (terms 5 and 6) significantly improved the model ($\chi^2(2) = 13.90, p = .032$). This is a simplification of our pre-registered exploratory analysis on learner scores (see Table S28 for the original pre-registered model).

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	1.13	0.21	5.44	1.52e-07
Intermediate Complexity	1.89	0.29	6.58	3.96e-10
High Complexity	2.35	0.29	8.09	5.60e-14
Communication	0.24	0.12	2.01	0.0454

Table S4: Experiment 1 concept regularization (Section 2.2.2). A nested model comparison confirmed that adding main effect of communication significantly improved the model ($\chi^2(1) = 11.4, p = .0432$).

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	0.90	1.60	0.56	0.57
Learner Concept	26.98	2.13	12.66	<0.001

Table S5: Experiment 1 correlation, predicting learner cumulative score from their concept knowledge.

Example Teachers

Score	Teacher Feedback
2	“Great! All triangles are positive except for filled in blue. ”
3	“Perfect. Outlined blue is the only square that is positive. In this example, all of the shapes on the bottom right would be positive. ”
1	“Try to avoid the solid filled in blue triangles! ”
4	“Awesome! Great job! ”
5	“Well done! ”
2	“Nice! Remember only the blue outlined squares are positive, all other squares are negative. ”
3	“Great job! ”
3	“Great! The only triangle that is not positive is the solid blue one, the pink one would be positive. ”
5	“Fantastic! ”
5	“Great job! :) ”

Table S6: Example linguistic messages from a “High” complexity pair in Experiment 1 (final score 33). The teacher initially taught a simplified version of the concept: after the first level, they sent “All triangles are positive except filled in blue.” They subsequently provided the rest of the concept: “Outlined blue is the only square that is positive.”

Score	Teacher Feedback
-2	“blue empty triangles, pink empty squares and triangles and pink filled in squares are positive”
3	“good job!!”
3	“gj! reminder: blue empty triangles, pink empty squares & triangles, pink filled in squares are positive”
-2	“reminder: blue empty triangles, pink empty squares & triangles, pink filled in squares are positive”
1	“gj! you could have went to the upper right corner which were all positive. reminder: blue empty triangles, pink empty squares & triangles, pink filled in squares are positive”
-2	“do your best! reminder: blue empty triangles, pink empty squares & triangles, pink filled in squares are positive”
1	“gj! the bottom left hand corner had more positive values, but you’re doing great :0 reminder: blue empty triangles, pink empty squares & triangles, pink filled in squares are positive”
2	“really good job! that corner had the most positive values :) reminder: blue empty triangles, pink empty squares & triangles, pink filled in squares are positive”
3	“great!! that corner also had the most positive values :) keep it up! reminder: blue empty triangles, pink empty squares & triangles, pink filled in squares are positive”
3	“yayy that was a really good job!! ty for cooperating :)”

Table S7: Example linguistic messages from a “High” complexity pair in Experiment 1 (final score 10). The teacher attempted to communicate the entire concept after the first level.

Appendix B: Experiment 2

This section contains full results, model details, and additional analysis for Experiment 2 (Section 3 in the main paper).

Complexity	Communication	Context	N	Accuracy		Cumulative Score		Learner Difficulty		Teacher Difficulty	
				Mean	SD	Mean	SD	Mean	SD	Mean	SD
Low	Language	Locations + Features	35	.84	.25	32.1	9.8	1.40	1.29	1.14	1.22
		Locations only	33	.72	.35	17.2	16.4	2.45	1.50	2.21	1.67
	Demonstration	Locations + Features	39	.85	.26	26.5	12.8	1.87	1.24	1.38	1.16
		Locations only	34	.76	.39	29.6	12.5	1.65	1.30	1.03	1.06
Intermediate	Language	Locations + Features	38	.82	.29	22.0	11.0	1.87	1.58	1.66	1.30
		Locations only	35	.40	.33	5.9	10.2	3.57	1.14	3.69	1.45
	Demonstration	Locations + Features	33	.39	.34	8.9	12.8	3.55	1.32	2.12	1.29
		Locations only	37	.43	.37	8.3	12.3	3.65	1.21	1.70	1.29

Table S8: Summary of conditions and results for Experiment 2.

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	0.76	0.05	15.37	< 2e-16
Context	0.42	0.05	8.68	< 2e-16
Communication	0.26	0.05	5.28	1.30e-7
Boolean Complexity	-0.69	0.05	-13.98	< 2e-16
Comm:Context	0.34	0.05	6.90	5.29e-12

Table S9: Experiment 2 transmission fidelity (Section 3.2.1), testing for an interaction effect of communication and context. A nested model comparison confirmed that adding the interaction effect significantly improved the model ($\chi^2(1) = 48.94, p < 2.65\text{e-}12$.)

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	18.84	0.74	25.43	< 2e-16
Boolean Complexity	-7.54	0.74	-10.16	< 2e-16
Communication	0.54	0.74	0.73	0.469
Comm:Context	4.13	0.74	5.58	5.74e-08

Table S10: Experiment 2 learner scores (Section 3.2.1). Interaction effect of communication and context. A nested model comparison confirmed that adding the interaction effect significantly improved the model ($\chi^2(1) = 4844.4, p = 1.63\text{e-}8$).

Appendix C: Experiment 2 Teaching Strategies

Demonstration Teaching

Besides the score-maximizing strategy described in the main text, we considered a *feature-maximizing* strategy: teachers could demonstrate by choosing the maximum number of distinct objects. Within our task, all score-maximizing demonstrations were also feature-maximizing (1078/1430, or 75%). There were an additional 122 demonstrations that were feature-maximizing (a total of 1200/1430, or 83%). A one-way ANOVA comparing the effect of condition on their number of feature-maximizing demonstrations did not show a significant difference ($F(3, 139) = 1.604, p = .191$).

Finally, we found that both criteria (number of *score*-maximizing and *feature*-maximizing demonstrations respectively) were negatively correlated with self-reported effort (see Tables S11 and S12). This suggests that most teachers were using these strategies (score- or feature-maximizing) and found that more or less difficult.

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	2.86	0.26	11.08	<0.001
Optimal Score	-1.73	0.32	-5.45	<0.001

Table S11: Experiment 2 Demonstration teacher difficulty-optimality analysis. Self-reported difficulty was inversely correlated with number of reward-maximizing demonstrations (“Optimal Score”).

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	3.62	0.38	9.59	<0.001
Optimal Features	-2.46	0.44	-5.66	< 0.001

Table S12: Experiment 2 Demonstration teacher difficulty-optimality analysis. Self-reported difficulty was inversely correlated with number of feature-maximizing demonstrations (“Optimal Features”).

Linguistic Teaching

This section contains additional information about linguistic teaching strategies in Experiment 2 (Section 3.2.3).

Figure S2: Total number of characters by teachers over the course of the experiment. *Locations only* teachers tended to send more characters, yet *locations and features* condition pairs learned more of the concept and scored higher.

Token	Count	Bigram	Count
triangle	146	good job	47
good	145	well done	42
square	138	great job	32
pink	105	empty triangle	30
job	94	blue square	24

Table S13: Top five tokens and bigrams from *locations and features* linguistic teachers. Teachers used shared abstract features (shape, color, fill) to communicate generalized information about which objects were positive.

Token	Count	Bigram	Count
one	279	bottom left	130
right	268	top right	122
left	251	bottom right	96
bottom	246	top left	80
positive	244	left corner	49

Table S14: Top five tokens and bigrams from *locations only* linguistic teachers. Teachers relied on spatial and behavioral references to specific items in order to communicate which ones were positive.

Score	Teacher Feedback
-3	“The squares were positive, triangles negative”
4	“Nice work!”
4	“Doing great”
4	“Keep it up”
1	“Dont forget you can hit two keys at once to move diagonally, which is faster”
2	“There you go”
3	“Nice. Take a second at the start to see which corner has the most value. This one was bottom right.”
3	“Very nice”
5	“Perfect! ”
5	“Another perfect one. Great job!”

Table S15: Example linguistic messages from a *locations and features* context, *low* complexity pair in Experiment 2 (final score 28). Pairs in this condition generally easily taught the concept in the first one or two levels.

Score	Teacher Feedback
-2	“The positive objects were in the left hand corner, apart from the one right in the corner itself.”
1	“The first object you got was negative, all the others in that top right corner were positive. ”
0	“The objects in the bottom left hand corner were positive, apart from the one right in the corner ”
2	“Good going, they were the right ones.”
0	“All the objects in the top right hand corner were positive”
2	“Good job, the second object was negative but the others were positive”
2	“Good work, you managed to avoid the negative object in that corner”
1	“all the objects in that corner were positive apart from the second one you took”
-1	“All the objects in the top left corner were positive.”
2	“Top right was the best corner, but good work.”

Table S16: Example linguistic messages from a *locations only* context, *low* complexity pair in Experiment 2 (final score 7). Pairs in this condition generally taught by referring to specific objects and indicating which were positive.

Score	Teacher Feedback
-3	“everything you collected was negative. the top left had all positive, except the top second from the left item. the bottom left was all positive except what was in the far bottom left corner ”
1	“okay this time everything in the bottom right corner was positive, so try going for shapes/colors that look like that. avoid the shapes/colors that were in the bottom left, those were all negative ”
3	“good job! this time in the bottom left there was only one negative in the very left bottom corner. hope that helps! ”
4	“it seems like you have the hang of this, but just to make sure, everything in the bottom left was negative and there is one negative below you right now ”
5	“nice :) again everything in the bottom left was negative ”
3	“you got it down ”
4	“nice! ”
4	“nice again ”
5	“nice ”
5	“awesome! thanks for the money ”

Table S17: Example linguistic messages from a *locations only* context, *low* complexity pair in Experiment 2 (final score 31). Pairs in this condition were sometimes able to teach the concept successfully.

Score	Teacher Feedback
3	“All 3 were pos, above and left of you if pos. Top left all pos apart from one on top right. Top right closest to corner neg, next 2 out pos, next 2 out the lower one is pos the other is neg. Bottom left all neg apart from the one in the centre of the cluster”
0	“First pos, second neg, third pos, fourth neg. Last remaining in top right is pos. Top left all pos apart from one furthest out. Bottom left all pos. Bottom right all neg”
2	“Both of those pos. Bottom left the one closest in the corner is neg the other 2 are pos. Bottom right the furthest out and furthest in are pos. Top right the top 2 neg, middle 2 pos, bottom 1 neg. Top left the 3 highest pos, 2 lower neg”
4	“All 4 pos, 1 left in top right is neg. (nice!) Top right 3 closest are pos others neg. Bottom left all neg. Bottom right closest to corner pos, middle of the top line pos rest neg”
5	“Nice top right all 5 were pos. Top left middle height one is pos and bottom left pos rest neg. Bottom right all neg. Bottom left lower most 2 pos, next 2 neg, highest right is pos.”
2	“First 3 positive, last was negative. Bottom right the outer most 2 pos, next 2 neg, closest to corner pos. Top right all neg apart from one directly out from the corner the furthest. Top left The top 2 neg. Middle 2 pos lowest neg”
4	“All 4 positive, well done. Bottom right closest to corner neg, next 2 out pos next 2 out neg. Top right the upper left most pos, lowest pos rest neg. Top right top 2 pos and middle lower pos rest neg”
4	“All 4 pos, well done, remaining one neg. Top right all neg. Top left all neg apart from lowest one on the left. Bottom left the lower 3 neg upper 3 pos Upper 2 sorry on bottom left”
5	“All pos, well done. Top right highest one neg, middle 2 pos, lower left pos, lower right neg. Bottom right all neg apart from 1 in the middle. Bottom right all neg apart from top right”
5	“All 5 pos well done. Top right all pos but the lowest right. Bottom right all neg apart from lowest centre. Bottom right all neg”

Table S18: Messages from a “locations only” context, “Low” complexity pair in Experiment 2 (final score 34). This teacher used language to indicate the value of every single object in the trial, using behavioral references (“First pos, second neg...”) to indicate objects the learner collected and spatial references (“Top left...”) to indicate ones the learner did not.

Score	Teacher Feedback
-1	“that was negative solid pinks and hollow blues are positive”
3	“nice nice”
2	“gj”
2	“good good”
2	“gj. that thing moves way too slow lol”
2	“not much to say since the shapes and values aren’t changing, at least on my end”
1	“good try”
2	“gj. remember hollow blues are positive too”
3	“yay 3 points”
3	“thus ends the journey of the world’s slowest robot”

Table S19: Example *locations and features* context, *intermediate* complexity pair from Experiment 2. Final score was 19. Linguistic teachers in this condition communicated primarily about object features (shapes and colors).

Score	Teacher Feedback
-3	“those shapes are negative points do not choose those next time ”
2	“those shapes are postive the shapes you were moving toward at end were negative ”
-1	“the first shape you chose was negative and second was positive ”
-1	“the only shape you chose was negative the rest of them in that same corner were all postive ”
0	“all the shapes you were going close to were negative ”
1	“the rest of the shapes in that corner you collected from were all negative, the one you chose was the only postive one ”
1	“very good, the one you chose was positive, whereas the two you passed between were negative ”
-1	“the first one you got was postive but other two negative ”
1	“the top left corner were all positive ”
-2	“that corner you got was all negative ”

Table S20: Example *locations only* context, *intermediate* complexity pair from Experiment 2. Final score was -3. Linguistic teachers in this condition struggled to communicate the concept via reference to specific objects.

	Contrast	Estimate	Std. Error	Statistic	Adj. p-value
1	demo features teacher - demo features learner	-1.42	0.33	-4.34	< 0.001
2	demo locations learner - demo features learner	0.10	0.32	0.32	1.000
3	demo locations teacher - demo features learner	-1.84	0.32	-5.78	< 0.001
4	lang features learner - demo features learner	-1.68	0.32	-5.29	< 0.001
5	lang features teacher - demo features learner	-1.89	0.32	-5.96	< 0.001
6	lang locations learner - demo features learner	0.03	0.32	0.08	1.000
7	lang locations teacher - demo features learner	0.14	0.32	0.43	1.000
8	demo locations learner - demo features teacher	1.53	0.32	4.79	< 0.001
9	demo locations teacher - demo features teacher	-0.42	0.32	-1.31	0.893
10	lang features learner - demo features teacher	-0.25	0.32	-0.80	0.993
11	lang features teacher - demo features teacher	-0.46	0.32	-1.46	0.827
12	lang locations learner - demo features teacher	1.45	0.32	4.49	< 0.001
13	lang locations teacher - demo features teacher	1.56	0.32	4.84	< 0.001
14	demo locations teacher - demo locations learner	-1.95	0.31	-6.29	< 0.001
15	lang features learner - demo locations learner	-1.78	0.31	-5.79	< 0.001
16	lang features teacher - demo locations learner	-1.99	0.31	-6.47	< 0.001
17	lang locations learner - demo locations learner	-0.08	0.31	-0.25	1.000
18	lang locations teacher - demo locations learner	0.04	0.31	0.12	1.000
19	lang features learner - demo locations teacher	0.17	0.31	0.54	0.999
20	lang features teacher - demo locations teacher	-0.04	0.31	-0.15	1.000
21	lang locations learner - demo locations teacher	1.87	0.31	5.95	< 0.001
22	lang locations teacher - demo locations teacher	1.98	0.31	6.32	< 0.001
23	lang features teacher - lang features learner	-0.21	0.31	-0.69	0.997
24	lang locations learner - lang features learner	1.70	0.31	5.46	< 0.001
25	lang locations teacher - lang features learner	1.82	0.31	5.83	< 0.001
26	lang locations learner - lang features teacher	1.91	0.31	6.13	< 0.001
27	lang locations teacher - lang features teacher	2.03	0.31	6.50	< 0.001
28	lang locations teacher - lang locations learner	0.11	0.32	0.36	1.000

Table S21: Experiment 2: Tukey HSD multiple-comparison results for difference in self-reported difficulty across conditions. “Features” denotes *features and locations*; “locations” denotes *locations only*. Comparisons described in the text are bolded.

Appendix D: Low-Effort or Confused Teachers

Examination of the chat messages produced by *language* teachers in Experiment 2 reveal several teachers who were ineffective for different reasons. Table S22 includes a per-condition breakdown of these teachers. Removing them from analyses did not affect key results for transmission fidelity (Table S23) or cumulative scores (Table S24).

We identified three general types of ineffective teachers. Some offered encouragement rather than teaching (Tables S25); others referred to object features the learner could not see (Table S26); and finally some simply did not try to teach (Table S27). The data release contains fields corresponding to these labels.

Context	Complexity	“Ineffective” Teachers	Total Pairs
Features + Locations	Low	0	35
Features + Locations	Intermediate	3	38
Locations only	Low	6	33
Locations only	Intermediate	8	35

Table S22: Experiment 2 breakdown of teachers who did not teach or used an invalid strategy.

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	0.81	0.05	15.43	< 2e-16
Context	0.43	0.05	8.29	< 2e-16
Communication	0.30	0.05	5.77	8.1e-9
Boolean Complexity	-0.72	0.05	-14.09	< 2e-16
Context:Comm	0.34	0.05	6.62	3.6e-11

Table S23: Experiment 2 “Transmission Fidelity” results after removing teachers who did not teach or used an invalid strategy (compare to Table S9). Removing these teachers did not affect key results.

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	19.14	0.77	24.99	< 2e-16
Boolean Complexity	-7.83	0.76	-10.28	< 2e-16
Communication	0.85	0.77	1.10	0.27
Context	3.39	0.77	4.43	1.41e-5
Context:Comm	3.91	0.77	5.10	6.54e-7

Table S24: Experiment 2 “Cumulative Score” results after removing teachers who did not teach or used an invalid strategy (compare to Table S10). Removing these teachers did not affect key results.

Score	Teacher Feedback
0	“Good try.”
3	“Good start ”
0	“Good try”
1	“You are doing great!”
-5	“Oops, wrong direction.”
0	“Better luck next time.”
-2	“Oops, you’re still great!”
-1	“We We’ll get ’em next time.”
-2	“We will do better next time.”
1	“Good start.”

Table S25: Example teacher (*Locations only* context, *low* complexity) who provided *encouragement* rather than teaching.

Score	Teacher Feedback
-2	“red is bad”
-5	“do not go to the red ”
4	“good only go to the green ”
4	“good, continue to only go to the green ”
5	“continue to the same plan ”
3	“good job, continue the same plan ”
4	“good job, continue the same plan ”
4	“good job, continue the same plan ”
5	“good job, continue the plan just one more level ”
5	“Good job ”

Table S26: Example teacher (*Locations only* context, *low* complexity) who did not understand the experiment condition and provided feedback about object features (red, green) which the learner could not see. In this case, the learner figured out the rule purely from individual learning.

Score	Teacher Feedback
-3	“”
4	“”
2	“”
2	“”
-4	“Hi ”
1	“”
3	“”
2	“”
3	“”
3	“”

Table S27: Example teacher (*features and locations* context, *intermediate* complexity) who simply did not try to teach.

Appendix E: Pre-Registered Exploratory Analyses

Our pre-registrations included an exploratory analysis on per-level scores. We hypothesized that there would be a difference in *learning rate*: that normalized learner scores on each level would increase faster in certain conditions than others. For Experiment 1, this entailed a three-way interaction between communication, complexity, and level number. For Experiment 2, this entailed a three-way interaction between communication, context, and level number. We pre-registered mixed-effects models predicting the per-level normalized score (points obtained / total possible points) from these variables and their interactions.

In practice, these models proved too complex: per-level scores were nonlinear, and the theoretically important differences were visible in participants’ final scores. Thus, we simplified the analysis to the fixed-effects models described earlier (Appendix A) and in the main text (Section 3.2.1). For completeness, we provide results for the original pre-registered analyses, as well as plots of per-level scores.

Figure S3: Normalized scores over the course of Experiment 1. Scores suggest in the “Low” difficulty condition both “Language” and “Demonstration” learners acquired the concept equally quickly. In the “Intermediate” and “High” difficulties, “Language” learners acquired the concept faster. However, the results were nonlinear.

Figure S4: Normalized scores over the course of Experiment 2. In the “Low” difficulty condition, “Partial”-“Language” learners fared worse than other conditions. In the “Intermediate” difficulty condition, “Full”-“Language” learners fared the best.

	Effect	Group	Term	Estimate	Std. Error	Statistic	DF	p-value
1	fixed		(Intercept)	13.96	2.94	4.75	709.07	2.41e-06
2	fixed		Boolean Complexity	-3.54	1.45	-2.44	709.07	0.014751
3	fixed		Communication	5.22	2.94	1.78	709.07	0.075669
4	fixed		Level Number	5.10	0.37	13.61	1850.00	< 2e-16
5	fixed		Complexity : Level	-0.70	0.18	-3.81	1850.00	0.000145
6	fixed		Complexity : Communication	0.87	1.45	0.60	709.07	0.546892
7	fixed		Communication : Level	0.79	0.37	2.10	1850.00	0.035941
8	fixed		Complexity : Communication : Level	0.18	0.18	0.97	1850.00	0.332609
9	random	Pair UUID	sd_(Intercept)	25.69				
10	random	Residual	sd_Observation	48.61				

Table S28: Experiment 1: Pre-registered mixed effects model predicting per-level normalized scores (Fig. S3). Mixed-effects regression predicting the players' normalized score on each level (total points obtained divided by possible number of points). We used a random effect for each pair, and fixed effects for Boolean complexity (treated as a continuous variable), communication modality (sum coded), level number (treated as a continuous variable), all two-way interactions, and the three-way interactions. Note that a similar model using dummy coding on Complexity conditions does detect a significant interaction effect at Intermediate complexity (same as in final scores).

	Effect	Group	Term	Estimate	Std. Error	Statistic	DF	p-value
1	fixed		(Intercept)	14.93	2.43	6.14	950.29	1.22e-09
2	fixed		Boolean Complexity	-17.71	1.75	-10.11	279.00	< 2e-16
3	fixed		Communication	0.09	2.43	0.04	949.75	0.97164
4	fixed		Level Number	5.03	0.31	16.40	2552.00	< 2e-16
5	fixed		Context	3.17	2.43	1.30	949.72	0.19328
6	fixed		Communication : Level	0.27	0.31	0.87	2552.00	0.38395
7	fixed		Communication : Context	10.33	2.43	4.24	949.45	2.40e-05
8	fixed		Level : Context	0.96	0.31	3.13	2552.00	0.00178
9	fixed		Communication : Level : Context	-0.08	0.31	-0.25	2552.00	0.80056
10	random	Pair UUID	sd_(Intercept)	25.47				
11	random	Residual	sd_Observation	46.98				

Table S29: Experiment 2: Pre-registered mixed effects model predicting per-level normalized scores (Fig. S4). We predict the players' normalized score on each level (total points obtained divided by possible number of points). We used a random effect for each pair, and fixed effects for Boolean complexity (treated as a continuous variable), communication modality (sum coded), context (sum coded), level number (treated as a continuous variable), all two-way interactions, and the hypothesized three-way interaction. Relevant two-way interactions, but not the hypothesized three-way interaction, were significant.

Appendix F: Experiment 2 Control for Spatial Reference

We conducted a followup experiment to assess whether our results from Experiment 2 generalize to a setting with more spatial structure. To accomplish this, we re-arranged the objects in a grid, so that each “cluster” of objects was in the form of a cross (e.g. “+”). This allows for canonical spatial reference to individual objects (e.g. “top”, “middle”, “left”...). Everything else about the experiment, including the objects themselves, was kept the same.

Our hypothesis was that—despite this additional spatial structure—removing abstract object features would still significantly impair linguistic teaching. We use a subset of the conditions in the previous experiment (“Language” teaching / “Intermediate” complexity) and predict that teachers with “Locations and Features” context will transmit significantly more information than learners with “Locations only” context.

Following the other analyses, we used a binomial logistic regression predicting the learner’s concept knowledge from the teacher’s context condition. The effect of context was significant (see Table S30).

For additional details, see the experiment pre-registration:

https://aspredicted.org/BTF_72G

Figure S5: Illustration of the replication with additional spatial structure. A: the original experiment distributed objects randomly in the corners, making it difficult to reference them spatially. B: the replication version used the same objects, but placed them in crosses, affording easier referential access via canonical terms (“top”, “left”, “middle”, etc).

Complexity	Communication	Context	N	Accuracy	
				Mean	SD
Intermediate	Language	Full	30	0.72	.31
		Partial	34	0.35	.32

Table S30: Summary of results for Experiment 2 replication. We recruited 160 participants; seven refreshed their browser and were paired twice. Excluding these participants, 128 completed the experiment, giving us a sample size of 64 pairs.

Term	Estimate	Std. Error	Statistic	p-value
(Intercept)	0.14	0.10	1.51	0.13
Context	0.78	0.10	8.17	< .001

Table S31: Experiment 2 replication - transmission fidelity. Context is dummy-coded with *locations and features* as the default. Even with additional spatial structure, *locations and features* teachers communicated significantly more of the concept than *locations only* teachers.

Score	Teacher Feedback
-3	“what you just selected are negative ”
2	“first 2 positive, last negative ”
2	“third one was negative ”
1	“you selected positive, the cluster bottom left was all negative ”
-3	“the cluster you went for was all negative. top right cluster was all positive ”
-2	“cluster you went for was one positive in center, with 4 negative around it ”
1	“first 2 were positive, last was negative ”
-1	“first 2 positive ”
3	“that cluster was all positive ”
5	“nice one ”

Table S32: Example linguistic messages from a *locations only* context pair in Experiment 2 replication (final score 5). The teacher did not exploit the additional spatial structure, instead primarily using behavioral references (informing the learner about the objects they chose to collect).

Score	Teacher Feedback
1	“You hit two positive and one negative. the very top one was negative. the left one you didn’t hit was negative and the right was positive. The top left group had the left one being negative and all the others positive. The bottom left was the same, the left one negative and the others positive The bottom right are all negative except for the middle. I’ll give you a moment before continuing in case you want to take notes. Good luck!”
4	“Nice job, all positive! the one you didn’t hit was negative. The bottom right was all positive The bottom left was all negative The top left had the top one as negative and the left one as negative, the others positive Good luck once again”
1	“The top one you hit was negative, the others were positive. The bottom one would have been positive and the one on your left negative The bottom left was all positive except for the left one The top right and bottom right were the same, middle and bottom positive and the others negative. Hope I’m giving clear enough explanations, best of luck with the next one”
4	“Excellent, all positive! the one you missed out on was negative. The top left had the top and left as negative, the others positive. The bottom left was all negative The bottom right had the top, left and right as negative, middle and bottom as positive. Good luck again :)”
4	“Great job, those were all positive. The bottom one was positive too. Top left had the top, left and right as negative, the middle and bottom as positive Bottom left were all negative Bottom right had the top and left as negative, the middle, right and bottom as positive. Good luck again”
1	“Nice one, you hit two positives. One was negative and the others you missed were negative too. The top right only had the middle one as positive The two bottom groups were the same. Top and left negative, middle, right and bottom positive. Hope I’m managing to help a bit! Good luck”
2	“Really great, you hit the positives in the group and missed all three negatives Top left had the top and left negative, the others positive. Bottom left had only the left negative Bottom right had the top, left and right negative, middle and bottom positive. Good luck!”
-3	“I’m afraid those were all negative, the whole block was. The top left only had the middle positive the bottom left had the top, left and right negative, the middle and bottom positive The bottom right only had the left negative. Good luck again!”
4	“Nice one, those were all positive, the whole block was The bottom groups were the same with only the middle being positive. And the top right had the top and left negative and the middle, right and bottom positive. Almost done now :) Great working with you, good luck!”
4	“Great, all positive! And the one you missed was negative :) Excellent job. The top right was all positive, the bottom right all negative The bottom left only had the middle positive. Great job all round, thanks :)”

Table S33: Example linguistic messages from a *locations only* context pair in Experiment 2 replication (final score 22). The teacher was able to exploit the additional spatial structure to communicate positive and negative examples.

References

Feldman, J. (2000). Minimization of boolean complexity in human concept learning. *Nature*, 407, 630–633. doi:[10.1038/35036586](https://doi.org/10.1038/35036586).