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Good-enough production: Selecting easier words instead of more accurate ones

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Data availability statement:

The data that support the findings of this study are openly available in a publicly accessible repository on the Open Science Framework (OSF) at <https://osf.io/3svge/>.

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Abstract

Dominant theories of language production suggest that word choice—lexical selection—is driven by alignment with the intended message: to talk about a young feline, we choose the most aligned word, *kitten*. Another factor that could shape lexical selection is word accessibility, or how easy it is to produce a given word (e.g., *cat* is more accessible than *kitten*). To test whether producers are also influenced by word accessibility, we designed an artificial lexicon with high- and low-frequency words with word meanings corresponding to compass directions. Participants in a communication game (total $N = 181$ adults) earned points by producing compass directions, often requiring an implicit decision between a high- vs low-frequency word. A trade-off was observed across four experiments, such that high-frequency words were produced even when less aligned with messages. These results suggest that implicit decisions between words are impacted by accessibility. Of all the times that people have produced *cat*, sometimes they likely meant *kitten*.

Keywords: *language production; lexical selection; artificial language game; word accessibility; word frequency*

Statement of Relevance

An important feature of language is flexibility—we have several words to describe almost any concept. Most language production theories assume that we choose words that best reflect our intended message. An alternative, drawn from theories of motor control, is that word choices also reflect efficiency, such as saying the common word *cat* instead of the more precise word *kitten*. To date it has been difficult to distinguish these theories. We developed a novel communication game in which players gave compass directions to elves digging for treasure. We manipulated features of the game to test whether players would prefer easy, well-practiced compass directions over rarer, more precise ones. We found that players frequently sacrificed precision for efficiency, even though precise directions earned more points in the game. These results shed new light on our word choices, including potential sources of miscommunication, and new insight on how language use may share features with motor control.

Introduction

Options for a behavior, such as which word to say or which hand to reach with, require a decision process. Recent theories of motor control have hypothesized probabilistic decision-making processes that maximize utility of actions in the face of uncertainty (e.g., Wolpert & Landy, 2012). Language production – whether signed, spoken, or written – is a form of action that offers abundant alternative behaviors to convey a message, including alternative words and phrases. Measuring the costs and benefits between alternatives has been difficult, because researchers must know the utility of alternative choices in conveying a producer’s intended message, which is not readily available.

Theories of word choice (lexical selection), have not favored the probabilistic approach seen in motor control research. In lexical selection accounts, early grammatical encoding processes settle on words to fit the message, and later processes develop the phonological code for overt production (Levelt et al., 1999). On this view, a speaker’s word choices, such as *cat* vs. *kitten*, are guided solely by which words best fit the intended message (i.e., “message alignment”), not by word “accessibility” factors such as a word’s frequency or length, which could affect ease of production. Probabilistic and interactive production approaches have been invoked to account for related phenomena, including findings that accessibility affects word order (Bock, 1982), speed of production (Sevold & Dell, 1994), and distributions of speech errors (Dell & Reich, 1981). However, within the domain of lexical selection itself, the dominant view is that the producer’s message drives word choice (Jescheniak & Levelt, 1994; cf. Dell, 1986). In this paper, we investigate whether lexical selection is determined by message alignment or is more probabilistic, as seen in the motor literature. The results have important

implications for the ways in which the uniquely human behavior of language production does and does not differ from other forms of action that are seen across species (MacDonald, 2013).

Several studies have investigated whether lexical selection is truly controlled by a single deterministic factor. Ferreira and Griffin (2003) examined errors in picture naming and found that speakers misnamed pictures more often when the phonological form of an incorrect competitor word had been primed than when it had not been primed. Ferreira and Griffin termed this result “good enough production,” meaning that beyond message alignment, the accessibility of phonological forms also affect lexical selection. Similarly, producers increasingly avoid difficult words more when describing pictures under phonological interference (Jaeger, Furth & Hilliard, 2012; Koranda & MacDonald, 2018; Rapp & Samuel, 2002), and learners will extend familiar morphemes to novel grammatical categories (Harmon and Kapatsinski, 2017). Together, these studies are consistent with an interactive process account of lexical selection (Dell, 1986), in which accessibility constrains producers’ word choices.

A limitation of these studies is that they have no independent assessment of message alignment, making it difficult to distinguish alignment and accessibility effects on lexical selection. There are reasons to believe that message alignment, e.g. between a stimulus picture and a word describing it, could vary across producers and contexts. Dialects and other variations in experience affect word use (Melinger, 2021), but they may also affect producers’ messages. Similarly, studies of word usage in different discourse contexts, e.g., saying *tummy* vs. *stomach* to different audiences (Stoll et al., 2009), could have either an accessibility or message alignment interpretation. More generally, highly accessible words might be chosen both because they fit the message and have been used frequently (Bock, 1982). Because of difficulties distinguishing

alternative accounts, studies promoting good enough production have had comparatively little influence on the deterministic approach to lexical selection.

Testing the hypothesis that speakers weigh both message alignment and production difficulty requires that we have evidence of both. This information would help quantify probabilistic decision processes. In other words, is lexical selection effectively a deterministic process except in unusual cases such as homophone production, or is probabilistic integration of several factors part of lexical selection, as is hypothesized in other motor behaviors?

To address this question, we designed a small artificial lexicon that allowed us to precisely manipulate the strength of both message alignment and accessibility in four experiments, in order to quantify the interplay between these factors. We assigned novel words equidistantly along a single, continuous semantic space—directions on a compass. Participants communicated compass directions via typed responses to help elves hunt for treasure. The task of using a small number of compass terms to describe many different directions resembles a common feature of everyday language. For example, the cities of Detroit and Pittsburgh are located at different precise compass directions from Chicago, but we can describe both of them as “east” of Chicago. We varied the frequency of the compass direction names in an initial training phase, thereby affecting participants’ practice with different words and thus their accessibility—the ease with which these words could be retrieved and produced. We then assessed lexical selection behavior in a “treasure hunting” communication game.

If production choices are driven only by message alignment, then participants should produce directions that best match the message prompt (compass arrow). However, if lexical selection also entails probabilistic integration of accessibility, then producers’ should sometimes respond with high-frequency words even when the low-frequency alternative is more aligned

with the message. Because our artificial lexicon exactly specified the messages in the compass points in both learning and test, and because we also controlled the relative frequency - and consequently the accessibility - of different words in the language, we can quantify how message alignment and frequency affect lexical selection in a way that has not been possible to date.

Experiments 1 and 2

Our small artificial lexicon contained four novel high-frequency and four novel low-frequency words, each of which referred to a precise direction on a compass. Experiment 1 tests the degree to which message alignment and word frequency affect participants' use of words in the language, and Experiment 2 replicates and extends our results to a different layout of compass points.

Method

Participants

Eighty-three University of Wisconsin-Madison undergraduates participated for course credit (39 in Experiment 1, 44 in Experiment 2, 51 female; mean age: 18.6 years). With one exception in each experiment, participants were native speakers of English. This and subsequent experiments were approved by the University IRB.

Materials

For each participant, eight novel words were drawn randomly from a set of 18 pseudo-words (*pim, dak, vorg, yeen, grah, skod, gled, veek, blit, peka, sarp, minada, hoon, clate, noobda, gorm, frabda, mog*) developed by Amato and MacDonald (2010). Each participants' set of eight words was randomly assigned to eight equidistant compass directions across the 360-

degree face of a compass image: 15°, 60°, 105°, 150°, 195°, 240°, 285°, and 330° (see Figure 1).

These compass positions were chosen to avoid translation to standard directions such as “north”.

Each direction was assigned to a high-frequency or a low-frequency category in one of two counterbalanced compass arrangements. In Experiment 1 (Figure 1A), the arrangement of low-frequency/high-frequency words was designed to maximize the number of compass regions in which a high-frequency word was adjacent to a low-frequency word. The arrangement in Experiment 2 (Figure 1B) created an even balance between trials in which a high-frequency word was adjacent to another high-frequency word vs. a low-frequency word (and vice versa).

Figure 1. The eight compass directions learned and word frequency assigned to each compass direction (HF = high-frequency; LF = low-frequency) during training in (A) Experiment 1 and (B) Experiment 2. Novel words shown are examples; each participant received a different random assignment of words for the eight compass directions.

Procedure

Participants played a game — programmed in PsychoPy (Peirce, 2007) — in which their job was to help elves hunt for gold by indicating a search direction for buried treasure. The experiment consisted of a Training Phase, in which participants were taught novel words for the 8 compass directions (see Figure 1), and a Treasure Hunt described as a language game, in which participants were tested on angles that varied in distance from the trained compass directions. All instructions and trials were presented on screen, and participants typed all responses. Typing is a common method in language production, and typing and speaking have been shown to produce comparable results in studies of production choices (Gennari et al., 2012). Typing is known to be sensitive to word frequency, including in tasks with nonwords (Baus, Strijkers, & Costa, 2013; Kapatsinski, 2010; Barry & Seymour, 1988).

Training Phase. Participants were first presented with each compass direction and its assigned word, and they typed each of the novel words into a text box. Next, participants completed a Word Learning training in which they were presented with one of the eight compass directions and chose which of two words (a target and foil) matched that direction. Participants typed their response into a text box prompt and received immediate feedback on their answer. Critically, words in the high-frequency condition occurred four times more frequently (as both a target and as a foil) than the low-frequency words. The Word Learning Phase proceeded in blocks of 20 trials presented in random order. Each block contained four presentations of each high-frequency word and one presentation of each low-frequency word. If participants scored below 80% on a 20-trial block, they were presented with another block of 20 Word Learning trials. Once participants achieved 80% accuracy on a 20-trial block, they proceeded to the Word Recall Phase.

In the Word Recall Phase, participants' explicit recall of the words for the eight compass directions was tested. Participants were prompted to recall each word via typed responses. If participants made an error, they returned to the Word Learning Phase. The Training Phase continued until participants achieved 100% accuracy on all 8 words during the Word Recall trials. Thus, all participants entered the Treasure Hunt having learned the word for each compass direction, but having experienced high-frequency words four times more frequently than low-frequency words.

Treasure Hunt. The Treasure Hunt contained two phases. The first phase was described to participants as a game directing elves hunting for gold. The game was designed to test participants' naming responses to new compass directions. Following the game, the second phase consisted of two test blocks designed to re-check participants' knowledge of the original trained compass directions.

The first phase of the Treasure Hunt contained two trial types: Near Distance trials and Far Distance trials. In Near Distance trials, participants described randomly generated angles that were clearly nearer to one of the 8 compass directions than to others (see Figures 2A & 2C). Each test stimulus direction was 0° to 11° away from a previously trained compass direction. For these trials, the 4:1 ratio of high-frequency to low-frequency words was maintained. Participants saw a compass direction near each high-frequency word 12 times and a compass direction near each low-frequency word 3 times, for a total of 60 test trials. For each trial, participants were asked to type a direction word into the text box based on the compass to direct a group of elves towards a hidden treasure. Trials timed out after 5s if participants did not begin typing.

Figure 2. Gray shading indicates directions tested on (A) Near Distance and (B) Far Distance trials in Experiment 1, with examples of a (C) Near Distance and (D) Far Distance trial during the Treasure Hunt. For directions tested, the same distance manipulation was introduced in all experiments. The frequency of the trained compass directions is shown with the configuration used in Experiment 1. Red (dark) compass points were trained four times as often as blue (light) points in the Training Phase. For experiment trials (C & D), participants saw only the direction in black. The two nearest compass directions and words in light blue (low-frequency) and light red (high-frequency) are added for illustration purposes and were not visible to participants.

In Far Distance trials, participants were tested with randomly generated angles that were close to the midline of two compass directions, between 11° - 22° from each, creating conflict between two words that could guide the elves (see Figures 2B & 2D; $n = 64$). On critical Far Distance trials, the angle fell between a low-frequency and a high-frequency word (Experiment 1: $n = 48$; Experiment 2: $n = 32$), though the compass direction always lay at least two degrees closer to one compass direction than another. The trial design and feedback were otherwise identical to Near Distance trials. In Experiment 1, participants saw the Near Distance trials, followed by the 64 Far Distance trials. In Experiment 2, participants first completed 20 Near Distance trials, to ensure that the task goal was clear to participants during the initial Treasure Hunt trials. On the remaining trials, Near Distance trials ($n = 40$) and Far Distance trials ($n = 64$) were randomly intermixed.

Feedback. To incentivize fast and accurate performance, participants in Experiments 1-2 received feedback in the form of a score after each trial (Figure 3A), with points proportional to participants' message alignment (how close the word was to the typed compass direction) and speed (how quickly participants completed typing the word). Participants' base score varied from 0 to 45 points based on the distance of the tested angle from the word entered, with closer labels yielding higher points (45 points = no difference between tested angle and the entered word's compass direction; 0 points = tested angle is 45° or more away from the entered word's compass direction). This base score was then scaled based on the speed of participants' responses. For example, a faster reaction time of 300 ms corresponded roughly to a 4% change in base score (0-3 points). Thus, while both speed and message alignment were emphasized, the scoring system weighed message alignment much more heavily than speed in assigning points. Participants

received a score of 0 if they did not complete typing before the trial timed out or if their response was a word that named a direction more than 45° from the indicated compass direction.

Figure 3. Example of immediate feedback (A) vs. intermittent feedback (B). In Experiments 1 and 2, participants received feedback after each game trial showing their response and gold coins earned (A). In Experiments 3 and 4, participants received no feedback after each response, and after every eight trials were shown the cumulative amount of gold coins earned during those trials (B).

Word retention. In the second phase of the game, participants were re-tested on their knowledge of the eight trained compass directions. The first eight retention trials (the 8 original compass directions, randomized) preserved task demands of the previous trials and from the participants' perspective were simply additional trials in the game. These trials thus provided a covert Timed Retention test. Participants were then introduced to a new block of trials described

as being separate from the treasure hunting game. This block served as an Untimed Retention test. Eight trials (the trained compass directions, randomized) appeared, and participants recalled the words without time limits. No feedback was presented.

Results

Word Training Performance

Participants' accuracy across all word learning blocks was high (Experiment 1: $M = 95.2\%$, $SD = 3.1\%$; Experiment 2: $M = 95.8\%$, $SD = 3.2\%$). On average, participants completed approximately 5 learning blocks (Experiment 1: $M = 4.59$, $SD = 1.93$; Experiment 2: $M = 4.36$, $SD = 2.62$) before reaching the required perfect performance on the recall test, progressing to the treasure hunt portion of the game.

Word Retention

At the end of the task, participants in both experiments showed high retention of both high-frequency (Experiment 1: $M = 97.4\%$, 95% CI = [94.8%, 100%]; Experiment 2: $M = 98.9\%$, 95% CI = [96.3%, 100%]) and low-frequency words (Experiment 1: $M = 97.4\%$, 95% CI = [94.8%, 100%]; Experiment 2: $M = 94.9\%$, 95% CI = [92.3%, 97.5%]) on the Untimed Retention test. These results suggest that participants maintained high levels of accuracy on both high- and low-frequency words at the end of the Treasure Hunt. High retention of the 8 compass directions across participants ensures that any shifts in decision boundary during the Treasure Hunt are unlikely to be driven by forgetting particular labels (particularly the low-frequency labels). Participants also showed no significant difference in how quickly they responded correctly to high-frequency and low-frequency words in the Untimed Retention task in either Experiment 1 or 2 (measured from the onset of a test prompt to the participant pressing the Enter

key after typing the word). On the timed retention block, accuracy and reaction times for high-frequency words were comparable, though participants' were slightly more accurate and faster to respond for high-frequency words than low-frequency words, collapsing across Experiments 1 and 2. There was no main effect of experiment version (Experiment 1 vs. 2) on accuracy and reaction times and no interaction between experiment version and frequency for either block, suggesting the general learning patterns were similar across experiments. See section S4 in Supplementary Materials for further details, including an overview of participants' recall and response times for high- and low-frequency words in the final two retention tests at the end of each experiment.

Test Performance

Our main question was whether word frequency experience during training would increase the likelihood of participants overextending high-frequency words during test (the first phase of the Treasure Hunt), including in situations when a more message-aligned word (closer on the compass) was available. To investigate participants' tendency to overextend words, we focused specifically on low-frequency/high-frequency trials, in which a compass direction was tested in between a low-frequency and a high-frequency trained direction. We considered participants' likelihood of choosing the word for the nearest trained compass direction, dependent on whether that compass direction was a high- or a low-frequency word, while controlling for the distance from the nearest learned compass direction. As a conservative test, we focused exclusively on trials in which participants chose one of the two principal direction words within 45° of the stimulus direction (Experiment 1: 94.4% of responses; Experiment 2: 93.8% of responses). All of the patterns of findings remain identical if all low-frequency/high-frequency trials are considered.

Experiment 1. We used the lme4 package version 1.1–27.1 in R to fit a logistic mixed-effects model predicting the likelihood of choosing the nearest word from Word Frequency (centered; High = 0.5 vs. Low = -0.5) and the distance of the stimulus from the nearest compass direction (Bates et al., 2015; R Development Core Team, 2021). We included by-subject and by-item random intercepts as well as by-subject random slopes for word frequency and distance. The likelihood of choosing the nearest word decreased with increasing distance from the nearest compass direction, $b = -0.23$, Wald 95% CI = $[-0.25, -0.20]$, $z = -16.89$, $p < .001$. Crucially, controlling for distance from the nearest principal direction, participants were more likely to use the nearest word when it was a high-frequency word compared to a low-frequency word, $b = 0.71$, Wald 95% CI = $[0.30, 1.12]$, $z = 3.37$, $p < .001$ (Figure 4A). This effect corresponded to an estimated 3.1° shift (95% CI = $[1.3^\circ, 4.9^\circ]$) in participants' decision boundary toward high-frequency words as compared to low-frequency words. There was no interaction between frequency and Near vs. Far Distance trials.

To ensure that this effect is not an artifact of participants' being slightly more likely to forget the low-frequency labels, we conducted a series of robustness checks. First, to account for the fact that participants varied in their final accuracy for each label in the Untimed Retention test, we fit the same model while controlling for participants' average final accuracy for the two compass directions to either side of the target angle on a given trial. We treated participants' average final accuracy on the two neighboring compass directions as a fixed effect, and also added a random slope for average final accuracy to the main model. The frequency effect in participants' choices remained highly similar ($b = 0.72$, Wald 95% CI = $[0.31, 1.13]$, $z = 3.41$, $p < .001$) even after controlling for participants' average final accuracy on the two neighboring compass directions.

Next, as an even more conservative test of the robustness of the frequency effect, we refit the original logistic mixed-effects model including only participants who successfully named all compass directions correctly in the Untimed Retention at the end of the experiment ($n = 34$). The effect held even after removing all participants who did not perfectly name all compass directions at the conclusion of the experiment, $b = 0.54$, Wald 95% CI = [0.16, 0.92], $z = 2.76$, $p = .006$.

Experiment 2. To test the impact of frequency on participants' overextension tendencies, we fit the same model as in Experiment 1. Controlling for angle distance from the nearest compass direction, participants were more likely to use the nearest trained word when it was a high-frequency word as compared to a low-frequency word, $b = 1.36$, Wald 95% CI = [0.75, 1.97], $z = 4.37$, $p < .001$ (Figure 4B). This effect corresponded to an estimated 7.2° degree shift (95% CI = [4.0° , 10.5°]) in participants' decision boundary for high-frequency words as compared to low-frequency words. There was no interaction between Near vs. Far Distance trials. The effect held after controlling for participants' average final accuracy on the two neighboring compass directions ($b = 1.36$, Wald 95% CI = [0.75, 1.97], $z = 4.38$, $p < .001$) and when including only participants ($n = 35$) with perfect accuracy in the Untimed Retention test at the end of the experiment ($b = 1.19$, Wald 95% CI = [0.66, 1.73], $z = 4.42$, $p < .001$).

Figure 4. Probability of choosing the nearest compass direction between a low-frequency and high-frequency word in (A) Experiment 1, (B) Experiment 2, (C) Experiment 3, and (D) Experiment 4. X-axis reflects distance from the nearest compass direction, in degrees, when the nearest direction was a high-frequency word (red) vs low-frequency (blue). Error bands represent $+1 / -1$ SEs. Dots represent individual participant responses and violin plots show the density of the response distribution, with distributions at the top of the plot corresponding to choices for the word corresponding to the nearest compass direction, and distributions at the bottom of the plot corresponding to selection of the compass direction that is farther away (i.e., less accurate).

Experiment 3

Experiments 1-2 showed that participants' word use was affected by the frequency of potential responses. One concern with our findings is that they may have been driven by the explicit feedback given on every trial, as such consistent feedback is not a regular feature of natural language use. If explicit feedback is a key explanation for our frequency effect, then intermittent feedback should reduce or eliminate the effect. Experiment 3 removed frequent feedback and provided only multi-trial, aggregated updates on scores.

Method

Participants

A new group of University of Wisconsin-Madison psychology undergraduate students ($n = 55$; 38 female; mean age: 18.9 years, $SD = 0.88$; 54 native speakers of English) participated for course credit. Four additional participants were excluded because they did not complete the study. The larger sample size was due to unintentional over-collection of data.

Design and Procedure

The experimental design and procedure was identical to Experiment 2, with the following differences. First, to prevent excessive perseverance on the learning block, a participant was limited to 10 learning test blocks before automatically advancing to the Treasure Hunt. Second, unlike in previous experiments, participants were instructed that they would receive intermittent feedback on their performance during the Treasure Hunt. A single, cumulative score was displayed every eighth trial (Figure 3B).

Results

Word Training Performance

Participants' accuracy across all pair learning blocks was high ($M = 94.4\%$, $SD = 4.2\%$). On average, participants completed around 5 pair learning blocks ($M = 4.64$, $SD = 1.99$) before progressing to the Treasure Hunt.

Word Retention

Participants' accuracy and response times were similar for high-frequency and low-frequency words on both timed and untimed trials at the end of the Treasure Hunt, with the exception that participants' were slightly faster to respond to high-frequency words during the Timed Retention test (see Table S3 in the Supplementary Materials for details).

Test Performance

To test the impact of frequency on participants' overextension tendencies, we fit the same model as in Experiments 1 and 2. Controlling for angle distance from the nearest compass direction, participants were more likely to use the nearest word when it was a high-frequency word as compared to a low-frequency word (Figure 4C), $b = 1.17$, Wald 95% CI = [0.58, 1.77], $z = 3.89$, $p < .001$. This effect corresponded to an estimated 6.0° degree shift (95% CI = [3.0° , 9.0°]) in participants' decision boundary for high-frequency words as compared to low-frequency words. The effect held after controlling for participants' average final accuracy on the two neighboring compass directions ($b = 1.21$, Wald 95% CI = [0.62, 1.80], $z = 4.05$, $p < .001$) and when including only participants ($n = 42$) with perfect accuracy in the Untimed Retention test at the end of the experiment ($b = 0.98$, Wald 95% CI = [0.34, 1.62], $z = 2.98$, $p = .003$).

Experiment 4

A concern about Experiments 1-3 is that familiarity of the trained compass direction is confounded with frequency of producing a word because every presentation of a compass direction was accompanied by the participant typing that direction's name. Thus, it is possible that the frequency effects in Experiments 1-3 are driven by familiarity with the visual stimuli rather than by word frequency. Therefore we added a new compass direction task to Experiment 4 in order to unconfound the frequency of visual stimuli and associated words.

Method

Participants

A new group of University of Wisconsin-Madison psychology undergraduate students ($n = 43$; 24 female; mean age: 18.7 years, $SD = 0.88$; all native speakers of English) participated for course credit.

Design & Procedure

The experiment design and procedure was identical to Experiment 3, with two main adjustments to the Training Phase described below.

Compass Practice Block. This new block preceded word learning and contained no words. On each trial, a compass circle was displayed and one of the eight compass directions appeared for 500 ms before disappearing. Next, a second randomly generated compass direction appeared from among the remaining seven compass directions. The participant was then instructed to adjust the angle to match the previous orientation by rotating the computer mouse click wheel. To ensure that participants only received exposure to the eight compass directions, the angle moved in 45° increments. Once the participant was satisfied with the angle position,

they left-clicked with the mouse to end the trial. Feedback then appeared on screen informing them of recall accuracy (correct or incorrect). Participants completed 100 trials, in random order.

In order to unconfound compass direction exposure and word frequency, the compass directions for which a low-frequency name would later be assigned appeared four times more often than the compass directions for which a high-frequency name would be assigned. This was true of both the targets displayed for 500 ms and also the starting position for participants' response. Thus after participants completed this Compass Practice block and the Word learning block, they had encountered each of the eight compass directions the same number of times. By contrast, the associated words for each compass direction were presented at either high or low frequencies, as in the previous experiments.

Word Learning Block. In order to match compass direction experience across high- and low-frequency words, it was necessary to fix the number of learning trial blocks for participants. In this experiment, participants advanced to the Treasure Hunt after five Learning Blocks, which was the modal number of learning blocks that participants completed in Experiments 1-3.

Results

Compass and Word Training Performance

Participants were highly accurate in their memory for compass directions ($M = 97.7\%$, $SD = 3.8\%$) and across all pair learning blocks ($M = 93.0\%$, $SD = 7.7\%$).

Word Retention

As in the previous experiments, retention for high- and low-frequency words did not differ significantly in either the Timed Retention or Untimed Retention tasks, although accuracies were

numerically higher for high-frequency words compared to low-frequency words (see Table S3 in the Supplementary Materials).

Test Performance

The model with the full random effects structure from Experiments 1 - 3 did not successfully converge, leading us to prune the random effects structure by removing the random slope for angle distance (the predictor of least theoretical interest) to achieve model convergence. The results including the full random effects structure from Experiments 1-3 yield qualitatively similar results. Controlling for angle distance from the nearest compass direction, participants were more likely to use the nearest word when it was a high-frequency word as compared to a low-frequency word (Figure 4D), $b = 0.77$, Wald 95% CI = [0.17, 1.38], $z = 2.51$, $p = .012$. This effect corresponded to an estimated 3.8° degree shift (95% CI = [0.8° , 6.8°]) in participants' decision boundary for high-frequency words as compared to low-frequency words. The effect held after controlling for participants' average final accuracy on the two neighboring compass directions ($b = 0.78$, Wald 95% CI = [0.17, 1.39], $z = 2.51$, $p = .01$). However, the effect of frequency was not significant when including only participants ($n = 33$) with perfect accuracy in the Untimed Retention test at the end of the experiment ($b = 0.42$, Wald 95% CI = [-0.19, 1.04], $z = 1.35$, $p = .18$), indicating that the effect was more sensitive to the inclusion of participants with imperfect final retention of all compass directions in Experiment 4.

Unlike in Experiments 1-3, participants could advance to the Treasure Hunt prior to achieving 100% accuracy on the eight compass directions during the Word Learning Phase, since the number of Word Learning blocks was fixed at five. We therefore additionally investigated whether the effect depended on the inclusion of participants who had not yet learned all compass labels perfectly. The effect of frequency remained similar even after removing all participants

who did not correctly label all words at the end of the Training Phase ($n = 29$), $b = 0.73$, Wald 95% CI = [0.02, 1.45], $z = 2.00$, $p = .045$.

General Discussion

Our novel language and communication game allowed us to quantify, for the first time, the degree to which language producers engage in probabilistic lexical selection and weigh both word accessibility and message alignment. In critical conditions across four studies, high-frequency words were favored over more precise low-frequency alternatives. This trade-off emerged even when participants knew low-frequency words well, as evidenced by performance on a post-test, and despite the fact that the point system in the communication game always rewarded message alignment more than speed. These results suggest that lexical selection can be characterized as “good enough” (Ferreira & Griffin, 2003), via probabilistic decision making that weighs message alignment and accessibility, broadly consistent with other accounts of action (Wolpert & Landy, 2012).

These results are consistent with prior evidence that phonologically-based accessibility factors may influence the choice of words in language production (Ferreira & Griffin, 2003; Jaeger, Furth & Hilliard, 2012; Koranda & MacDonald, 2018; Rapp & Samuel, 2002). Our work extends these findings to effects of word frequency (see also Harmon & Kapatsinski, 2017) and furthermore quantifies the degree to which accessibility results in deviations from message alignment, owing to unique design features of our paradigm that allowed independent manipulation of message and accessibility. More work is needed to determine how consistently these effects appear across populations and various communication situations. For example, while our effects were consistent across several variants of the game, one important step is to extend these results to other modalities of language communication such as speech and sign.

These findings are related to several other language production phenomena, though more work is needed to determine whether similarities reflect related underlying processes. For example, this work may provide insight into some types of speech errors. When speakers make word-substitution errors, such as saying *salt* when *pepper* is intended, a higher-frequency word tends to replace a lower-frequency intended word (Harley & MacAndrew, 2001). This outcome might reflect the same probabilistic decision making that we advocate here, in which a more accessible word is chosen over a more accurate but less accessible alternative, such as speakers' use of high-frequency words like *cat*, instead of the less accessible but more accurate word, *kitten*. Relatedly, children are sometimes found to produce overextensions for frequent words (e.g., calling a sheep a *dog*) despite comprehending the relevant word meanings (Gershkoff-Stowe et al., 2006; Naigles & Gelman, 1995).

Our results have several implications for theories of language production. First, feed-forward models of language production in which lexical selection is influenced only by message alignment and not by linguistic form (e.g., Levelt et al., 1999) do not predict our finding that implicit production choices balance message alignment and accessibility. Other accounts suggest that word form has only a limited effect on lexical selection because selection is generally completed before word-form computations have begun (e.g., Dell & O'Seaghdha, 1991; Goldrick, 2006). The consideration of lexical selection as a form of probabilistic decision making may be broadly consistent with this view, but our findings that lexical selection shifts away from message alignment suggests that weighing of multiple factors may be more pervasive than these theories have posited.

Second, this work places constraints on the extent to which language production accommodates the listener's perspective (Arnold, 2008). While an accessible, but less accurate

word would not benefit the comprehender, our results suggest such trade-offs might be communicatively optimal. Piantadosi et al. (2012) present computational simulations showing that selection of vague, common words over rare precise ones can result in a more efficient communicative system (see also MacDonald, 2013, who argued that increased efficiency for the producer aids the comprehender). In our communication game, points awarded for message alignment reinforce accurate communication to elf “listeners”, yet participants still selected frequent words. Other studies have shown that producers regularly produce ungrammatical phrases, impairing comprehension but easing the task for the producer (Morgan et al. 2020). Together with our results, such findings suggest that people may routinely generate utterances that are easier to produce and “good enough” to communicate a message, despite increasing comprehension difficulty.

This work also has implications for how language production processes modulate language change over time (MacDonald, 2013). Probabilistic decisions favoring more accessible, high-frequency words may account for how the meaning of accessible words changes (Bybee, 2008) or how grammatical patterns are regularized over generations of use (Hudson Kam & Newport, 2005). Recently, Harmon and Kapatsinski (2017) showed that when two semantically equal options could describe a novel meaning, the high-frequency one was more reliably extended. Consistent with Bock’s observation (1982), links between concepts and words may become stronger for frequent compared to infrequent words, or high activation can itself become a probabilistic cue to message alignment. Our results suggest such extensions may occur even when high-frequency words are actually less precise, predicting a robust influence of frequency on diachronic change.

In summary, our data reveal that lexical selection is not deterministically driven by alignment with a message but is instead good enough—a probabilistic compromise between utility and efficiency. In other words, what we say is not always what we mean. Because similar utility-efficiency trade-offs also arise in nonlinguistic motor behaviors in humans and other species, this work narrows the range of production behavior that is unique to human language.

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Supplementary Materials

All analysis results (including additional detail beyond the material presented here) can be found in our publicly available data and analysis scripts:

- OSF: <https://osf.io/3svge>
- R Markdown Analysis Walkthrough: https://rpubs.com/zcm/good_enough_production

S1: Main logistic mixed-effects analyses in Experiments 1-4

S1.1. Overview over modeling results.

Table S1.

Estimates for the logistic mixed-effects model predicting the effect of word frequency on word choice in Experiments 1-4

Coefficient	Estimate	SE	z	p
Experiment 1				
Intercept	2.34	0.12	19.17	<.001
Word Frequency	0.71	0.21	3.37	<.001
Stimulus Distance	-0.23	0.01	-16.89	<.001
Experiment 2				
Intercept	1.98	0.13	15.11	<.001
Word Frequency	1.36	0.31	4.37	<.001
Stimulus Distance	-0.19	0.01	-13.48	<.001
Experiment 3				
Intercept	2.30	0.14	16.42	<.001
Word Frequency	1.17	0.30	3.89	<.001
Stimulus Distance	-0.20	0.01	-14.20	<.001
Experiment 4				
Intercept	2.26	0.14	15.89	<.001
Word Frequency	0.77	0.31	2.51	.01
Stimulus Distance	-0.20	0.01	-15.99	<.001

S1.2. Computing the decision boundary shift

In interpreting the parameter estimate of the frequency effect, we establish the corresponding shift in decision boundary in terms of distance from the nearest compass direction. This shift in decision boundary is computed from the parameter estimates (beta coefficients) of the logistic mixed-effects model estimating the difference between frequency conditions (the main model in the paper). To compute the decision boundary shift, we answer the following question: what shift in angle distance (from the nearest compass direction) corresponds to moving from the low-frequency condition (coded as -0.5) to the high-frequency condition (coded as 0.5), based on the model predictions? Model predictions are based on the fixed effects of the model (predictions are in logit/ log-odds space in logistic regression):

$$\text{logit}(Y) = b_0 + b_1 * \text{condition} + b_2 * \text{distance}$$

In particular, we are asking what adjustment c to *distance* allows the prediction for the low-frequency condition (*condition*=-0.5) to be equal to the prediction for the high frequency condition (*condition*=0.5). This means that the decision boundary shift c can be determined by solving the following equation:

$$b_0 + b_1 * 0.5 + b_2 * (\text{distance} + c) = b_0 + b_1 * (-0.5) + b_2 * \text{distance}$$

This equation can be simplified to:

$$c = -\frac{b_1}{b_2}$$

95% confidence intervals for the decision boundary shift are computed analogously using the confidence bounds of the model parameter estimates.

S2: Latency Analyses during the Treasure Hunt Phase.

For each experiment we investigated participants' speed in responding on trials in which they chose the nearest word (thereby maximizing message alignment). We fit linear mixed-effects models predicting participants' reaction times from Word Frequency (centered; High = -0.5 vs. Low = -0.5) and Distance from Nearest Principal Direction, including by-participant and by-item random intercepts and a random slope for Word Frequency. Error degrees of freedom were obtained using the Satterthwaite approximation with the help of the R package lmerTest (version 3.1-3; Kuznetsova et al., 2017). In all four experiments, participants responded faster when the nearest principal direction was a high-frequency word compared to a low-frequency word, and slower as the test stimulus' distance from the nearest principal direction increased (see Table S2). The effects were similar for both the Far Distance trials and the Near Distance trials in each experiment (no near vs. far trial type by frequency or distance interaction).

Table S2

Mean Reaction Times and linear mixed-effects model results comparing High-Frequency (HF) and Low-Frequency (LF) Compass Directions

Experiment	HF words	LF words	Model result
Experiment 1	2208ms [2160ms, 2256ms]	2663ms [2577ms, 2749ms]	$b = -405.4$, Wald 95% CI: [-525.6,-285.2], $t(39.9) = -6.61, p < .001$
Experiment 2	2278ms [2220ms, 2336ms]	2501ms [2397ms, 2605ms]	$b = -220.3$, Wald 95% CI: [-349.9,-90.7], $t(33.2) = -3.33, p = .002$
Experiment 3	2289ms [2237ms, 2341ms]	2573ms [2488ms, 2658ms]	$b = -257.8$, Wald 95% CI: [-349.0,-166.6], $t(54.7) = -5.54, p < .001$
Experiment 4	2262ms [2205ms, 2319ms]	2565ms [2471ms, 2659ms]	$b = -251.0$, Wald 95% CI: [-367.7,-134.4], $t(36.8) = -4.22, p < .001$

Note. Values in square brackets represent 95% within-participants confidence intervals (Morey, 2008).

S3: Overview of Performance in the Word Learning and Word Recall Blocks during the Training Phase.

Figure S3.1. Accuracy during Word Learning blocks in (A) Experiment 1, (B) Experiment 2, (C) Experiment 3, and (D) Experiment 4. The dashed line represents chance performance (since participants were prompted with two possible labels). Error bars represent 95% CIs. Numbers indicate the number of participants who completed each Word Learning block.

Figure S3.2. Accuracy during Word Recall Blocks in (A) Experiment 1, (B) Experiment 2, (C) Experiment 3, and (D) Experiment 4. Error bars represent 95% CIs. Numbers indicate the number of participants who completed each Word Recall block.

S4: Overview of Performance on Word Retention Trials.

Table S3

Mean Accuracy and Reaction Times (correct trials) and linear mixed-effects model results comparing High-Frequency (HF) and Low-Frequency (LF) Compass Directions in Untimed and Timed Retention

Test Block	HF words	LF words	Model result
Experiment 1			
Timed Retention			
Accuracy	91.7% [86.6%, 96.7%]	84.6% [79.5%, 89.7%]	$b = 0.59, z = 1.30, p = .19$
Reaction Time	2315ms [2173ms, 2458ms]	2583ms [2440ms, 2726ms]	$b = -205.3, t(120.0) = -2.11, p = .04$
Untimed Retention			
Accuracy	97.4% [94.8%, 100%]	97.4% [94.8%, 100%]	$b = -1.12, z = -0.30, p = .76$
Reaction Time	2726ms [2470ms, 2982ms]	3050ms [2795ms, 3306ms]	$b = -295.4, t(32.4) = -1.58, p = .12$

Test Block	HF words	LF words	Model result
Experiment 2			
Timed Retention			
Accuracy	93.8% [88.8%, 98.7%]	84.7% [79.7%, 89.6%]	$b = 0.75, z = 1.42, p = .16$
Reaction Time	2303ms [2169ms, 2438ms]	2436ms [2301ms, 2570ms]	$b = -99.3, t(17.1) = -0.99, p = .34$
Untimed Retention			
Accuracy	98.9% [96.3%, 100%]	94.9% [92.3%, 97.5%]	$b = 6.2, z = 1.85, p = .06$
Reaction Time	2684ms [2478ms, 2890ms]	2812ms [2606ms, 3017ms]	$b = -118.3, t(32.8) = -0.86, p = .40$
Experiment 3			
Timed Retention			
Accuracy	91.8% [87.5%, 96.2%]	89.5% [85.2%, 93.9%]	$b = 0.12, z = 0.17, p = .87$
Reaction Time	2217ms [2113ms, 2321ms]	2413ms [2309ms, 2517ms]	$b = -190.2, t(26.5) = -2.31, p = .029$
Untimed Retention			
Accuracy	97.7% [95.0%, 100%]	95.0% [92.3%, 97.7%]	$b = -0.42, z = -0.33, p = .75$
Reaction Time	2559ms [2414ms, 2703ms]	2505ms [2360 ms, 2649ms]	$b = 46.2, t(174.9) = 0.43, p = .67$
Experiment 4			
Timed Retention			
Accuracy	92.4% [88.2%, 96.7%]	83.1% [78.9%, 87.4%]	$b = 1.22, z = 1.77, p = .08$
Reaction Time	2342ms [2233ms, 2452ms]	2455ms [2346ms, 2565ms]	$b = -1.36, t(75.5) = -1.66, p = .10$
Untimed Retention			
Accuracy	97.7% [93.6%, 100%]	91.9% [87.8%, 95.9%]	$b = -3.89, z = -1.58, p = .11$
Reaction Time	2567ms [2387ms, 2747ms]	2691ms [2511 ms, 2871ms]	$b = -134.9, t(48.05) = -1.14, p = .26$

Note. Values in square brackets represent 95% within-participants confidence intervals (Morey, 2008).

S5: Additional covariates in the main logistic mixed-effects analyses in Experiments 1-4

Word length. The target labels used to identify compass directions in the present experiments (*pim, dak, vorg, yeen, grah, skod, gled, veek, blit, peka, sarp, minada, hoon, clate, noobda, gorm, frabda, mog*) varied in character length across participants. While labels were randomly assigned to compass directions across participants, and the variation in character length was generally small, we conducted additional exploratory analyses to ensure that the effect of frequency on lexical selection was robust to variability in word length. In the main logistic mixed-effects analyses demonstrating the effect of word frequency on lexical selection, we also fit models controlling for the character length of the nearest compass direction. In these models, we included the character length of the nearest compass direction as a fixed effect, as well as a by-participant random slope for character length (since character length varied within

participants). All effects held after controlling for character length, and we found no significant effects of character length (all $ps > .22$).

Number of word learning blocks during training. Participants varied in the duration of their training in Experiments 1, 2, and 3. The extent to which participants were trained on the compass directions may have influenced the degree to which participants exhibited a frequency effect on lexical selection. In the main logistic mixed-effects analyses demonstrating the effect of word frequency on lexical selection, we also fit models controlling for differences in training duration by including the number of training blocks as a fixed effect. All effects held after controlling for number of word learning blocks during training, with no significant effects of number of word learning blocks in Experiments 1-3 (all $ps > .14$).

S6: Details on the scoring system during the Treasure Hunt Phase

Participants received a graded reward (points) contingent on message alignment and speed during the Treasure Hunt. For a given response, participants' score was a product of a base score corresponding to message alignment (how close the word was to the typed compass direction) and response speed (how quickly participants completed typing the word). The arc (in degrees) between the tested angle and the word entered determined base score (0-45), with closer labels yielding more points. This base score was then scaled by the speed of participants' responses using the following formula:

$$\text{score} = \text{base score}_{\text{distance}} * \left(1 + \frac{\text{response limit} - \text{response speed}}{\text{response limit}}\right)$$

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