Evaluating GPT Surprisal, Linguistic Distances, and Model Size for Predicting Cross-Language Intelligibility of Non-Compositional Expressions

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Abstract

Cross-language intelligibility is defined as the ability to understand related languages without prior study. This study investigates how and to what extent linguistic distances and surprisal values generated by GPT-based models predict cross-language intelligibility of microsyntactic units (MSUs), a type of non-compositional expression characterized by syntactic idiomaticity. We compare performance across two research questions: (1) How well do linguistic distances and surprisal values from GPT-based models predict intelligibility of non-compositional expressions? (2) Does model size impact prediction performance of GPT-based surprisal? The predictors were tested on two experimental conditions (spoken input vs. combined spoken-written input) and two tasks (free translation and multiple-choice) with native Russian participants translating MSUs across five Slavic languages: Belarusian, Bulgarian, Czech, Polish, and Ukrainian. Results revealed that although GPT-based surprisal is a significant predictor of MSU intelligibility, the most crucial predictor is linguistic distances, with variations based on experimental conditions and task types. Additionally, our analysis found no substantial performance gap between smaller and larger GPT models.

1 Introduction

Cross-language intelligibility refers to the ability of speakers to understand related languages without prior study (Doyé, 2005; Gooskens and van Heuven, 2021). It is influenced by phonological, lexical, and orthographic similarities, particularly among languages with close typological proximity (Gooskens and van Heuven, 2021; Stenger and Avgustinova, 2021). Speakers can leverage these factors to recognize cognates, decipher grammar, and infer meanings, making comprehension or intelligibility across related languages achievable without any prior exposure to the language.

Cross-language intelligibility becomes significantly more challenging in case of *non-compositional expressions*, like microsyntactic units (Avgustinova and Iomdin, 2019). Non-compositional expressions have meanings that cannot be inferred from their individual components (Baldwin and Kim, 2010; Jackendoff, 2002; Kudera et al., 2023), often requiring cultural or contextual knowledge for proper interpretation. Microsyntactic units, a specific type of non-compositional expression used as our experimental stimuli, are characterized by their *syntactic idiomaticity*, where the structure itself carries figurative meaning (Iomdin, 2015, 2016; Avgustinova and Iomdin, 2019). Some examples of microsyntactic units in English are *'at the end of', 'to begin with', 'in spite of.'*[1]

Cross-language intelligibility of non-compositional expressions has been extensively explored in relation to various factors, including *linguistic distances* and *surprisal*. These factors are considered key indicators of how challenging an expression is to comprehend (Stenger et al., 2017; Jágrová et al., 2018). This is because linguistic distances capture differences and similarities across languages at the form level, including lexical, orthographic, phonetic, and phonological distances, while surprisal, a concept rooted in psycholinguistics and computational modeling, provides insight into cognitive processing difficulty and can serve as a proxy for the difficulty of processing foreign expressions (Jágrová et al., 2018). High-surprisal sequences are more cognitively demanding, as they deviate from predictable patterns.

Although these factors have been previously shown to correlate with the intelligibility of non-compositional expressions Zaitova et al. (2024a,b), it remains underexplored how these factors com-

[1] More examples of microsyntactic units in Slavic languages are given in Appendix A.

pare for experiments with different types of input.

Among all linguistic distances available, we focus specifically on orthographic and phonological distances. This choice was motivated by the following considerations. First, the non-compositionality of the microsyntactic stimuli make lexical distance measures less informative (Cutting and Bock, 1997; Wray, 2002). Second, phonetic distances, while relevant for language processing, are difficult to reliably measure in the context of unfamiliar languages (Best, 1995). Third, orthographic and phonological similarities have been shown to be particularly salient in studies of cross-language intelligibility (Vanhove and Berthele, 2015; Möller and Zeevaert, 2015; Gooskens and Swarte, 2017).

Despite the contribution of surprisal in cross-language intelligibility and expressions, it may also be influenced by the size of language models, from which surprisal is derived, and consequently its contribution performance. Recent advances in language modeling include large-scale transformer models like GPT (Radford and Narasimhan, 2018). While these large models excel in generating complex and contextually rich sequences, it is often suggested that surprisal values from smaller models may better predict human cognitive processes (Oh and Schuler, 2023a,b; Vafa et al., 2024).

Yet, previous findings of how model size influence surprisal's performance were about human reading time and native language comprehension. How model size relates to cross-language intelligibility, a comprehension across language instead of native comprehension, remains intriguing and needs to be explored. Therefore, in this study, we also investigate whether surprisal estimates from different-sized monolingual Russian (RU) GPT models (ruGPT-3-small and ruGPT-3-large) contribute differently to explaining human performance when interpreting non-compositional expressions, in particular microsyntactic units, across foreign, but closely-related languages.

Thus, in this study, we aim to fill in the above gaps by addressing the following research questions (RQs):

- **RQ1:** How well do linguistic distances and GPT-based surprisal predict cross-language intelligibility of non-compositional expressions in relation to different types of input?
- **RQ2:** Is the small variant of GPT model more effective than the large one in predicting intelligibility outcomes?

We conducted two experiments to evaluate the intelligibility of non-compositional expressions with spoken input only (Experiment 1), and with written input alongside spoken input (Experiment 2). Both experiments contain two tasks: free translation and multiple-choice question (MCQ). In the free translation task, participants need to listen to or read a foreign expression presented in a sentential context and generate a RU translation. In the MCQ task, participants need to select between a correct non-compositional translation and a literal, incorrect translation of the expression in the foreign language. RU native speakers were recruited as participants to translate the expressions from five Slavic languages, i.e., Belarusian (BE), Bulgarian (BG), Czech (CS), Polish (PL), and Ukrainian (UK).

By combining linguistic distances and surprisal values as predictive factors, we aim to provide a comprehensive view of the interplay between structural similarity and cognitive difficulty in cross-language intelligibility of non-compositional expressions with different types of inputs. Our study contributes insights into psycholinguistic modeling and the role of model scale in predicting cross-language intelligibility, offering both theoretical and practical implications.

2 Methodology

2.1 Stimuli preparation

2.1.1 Written data

To prepare our non-compositional expression stimuli, we selected 60 most frequent microsyntactic units per target language from an existing dataset with RU microsyntactic units and their translational equivalents in BE, BG, CS, PL, and UK (Zaitova et al., 2023). An example of a microsyntactic unit from the stimuli is: BE – ўвесь час , BG – не веднъж, CS – ne jednou, PL – niejednokrotnie, RU – не раз (English translation: not once). Further examples are given in Appendix A. The dataset provides not only the mapping between the RU units and their translational equivalents in the target Slavic languages but also a contextual sentence for the units with average lengths varying between 11 and 15 words and accompanied by its non-compositional RU equivalent.

2.1.2 Spoken data

We recorded the context sentences (containing the target units) using native speakers (one per target language) in self-paced reading sessions. All recordings were made in a controlled acoustic environment to ensure consistency across the samples. A 44.1 kHz sampling rate in an uncompressed format was used. Audio lengths averaged about 5–7 seconds. The speakers for BG, CS, and UK were female and those for BE and PL were male. The reason for BG and PL speakers being male is that we encountered difficulties finding female native speakers. The speakers' ages ranged from 21 to 29 (*mean*=25). This narrow age range helps minimize variability due to age differences in speech production.

2.1.3 Literal translation options for the multiple-choice task

The MCQ task mentioned in Section 1 requires participants to choose between two options: a correct translation and a literal counterpart. The correct translations were the translational equivalents described in Section 2.1.1, while the literal translation mimics the form of the stimulus but provides an inaccurate compositional translation of the expression. To create the literal translations, we utilized word-by-word translations sourced from Glosbe (`https://glosbe.com`) and checked with Vasmer's dictionary (`https://lexicography.online/etymology/vasmer/`). This experimental setting challenges participants to distinguish between non-compositional (correct) and literal (incorrect) options. Although a binary choice is limited, it served as a baseline measure for distinguishing idiomatic meanings from surface-level compositional interpretations. It aims to assess participants' ability to grasp nuanced, non-compositional meanings beyond surface-level comprehension.

2.2 Experimental setup

We conducted two web-based experiments with different types of input, namely Experiment 1 for spoken-only input and Experiment 2 for written input alongside spoken input, and with the two tasks (free translation and MCQ) mentioned in Section 1. The experiments were prepared via the website `[thelinkisanonymized]`. Before the experiments, participants first received instructions in RU detailing the tasks and procedures. After familiarizing themselves with the tasks, participants were required to register on the website and to complete a questionnaire in order to monitor their language background and to exclude those who had prior knowledge of the target languages, thereby maintaining the purity of the experiment's conditions.

Both experiments had similar interface and the same tasks. An illustration of the two experiments and the two tasks is shown in Fig. 1. The only difference between the two experiments is whether participants were additionally presented with the written form of the test units, comparing Fig. 1 (a) and (b) for Experiment 1 (left pannel) to Fig. 1 (c) and (d) for Experiment 2 (right panel). Note that participants were informed which language the test expression belonged to but were not told if their response was correct.

Further, in both experiments, participants received the free translation task first. They were first presented with an audio clip containing the expression presented in its contextual sentence together with the free translation task, as shown in Fig. 1 (a) and (c), i.e., the upper panel. The time to enter the translation was based on a formula of 10 seconds per word in a test unit plus an additional 3 seconds per word in its context. Participants were allowed to replay each audio fragment of the whole contextual sentence and of the test unit up to three times, simulating real-life scenarios where listeners can ask speakers to repeat themselves.

After the free translation task of each expression, participants received the MCQ for the same expression. This ensured that participants attempted a genuine interpretation before choosing between correct and literal translations. MCQ is illustrated in Fig. 1 (b) and (d), i.e., the bottom panel. It asked participants to choose from two options in RU that they believed to be correct: (i) the correct non-compositional equivalent translation and (ii) an alternative word-by-word literal translation, which was semantically inaccurate as explained in Section 2.1.3. The MCQ task aimed to assess participants' preference for the non-compositional (correct) translation over the literal (incorrect) one.

In total, each participant received 60 test units, each presented in a separate trial, together with their sentential context (in audio form). These 60 test units were evenly distributed across the five target languages. This means that each participant received 12 test units per target language, which is a random subset of the five subsets per target language.

2.3 Participants

We recruited native RU speakers as our participants via Prolific (https://prolific.com), an online

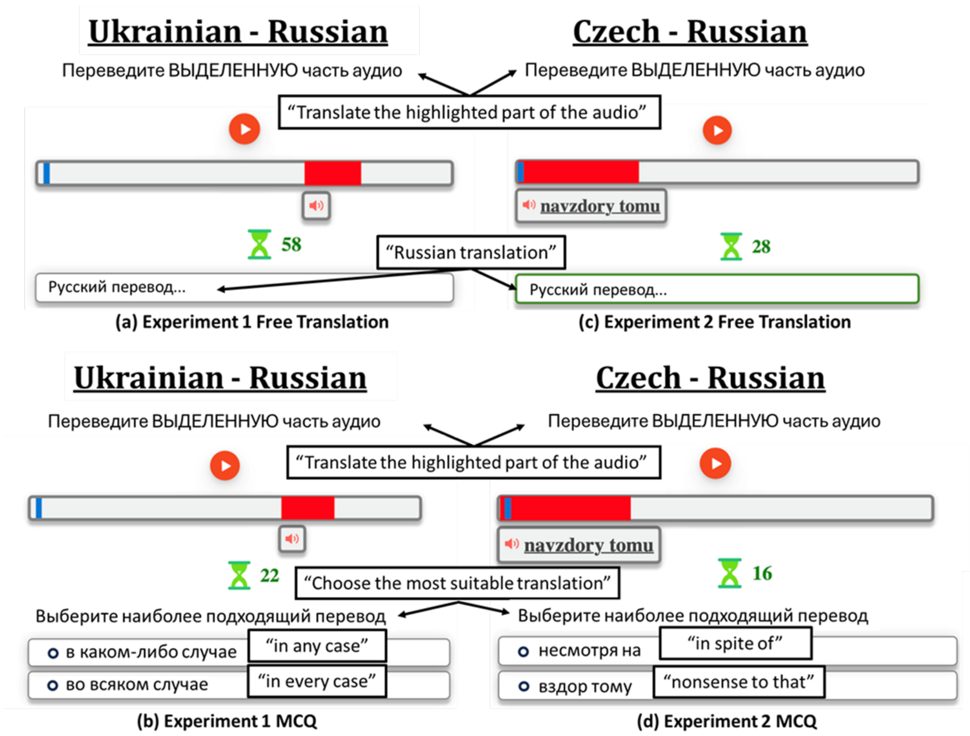


Figure 1: Task interface for the free translation and MCQ tasks received by Russian participants. The Czech test expression with written form in (c) and (d) is 'in spite of'. In the free translation task (a, c), participants' translation is to be typed in the white box. The green hourglass shows how many seconds are left for the participant to give their answer.

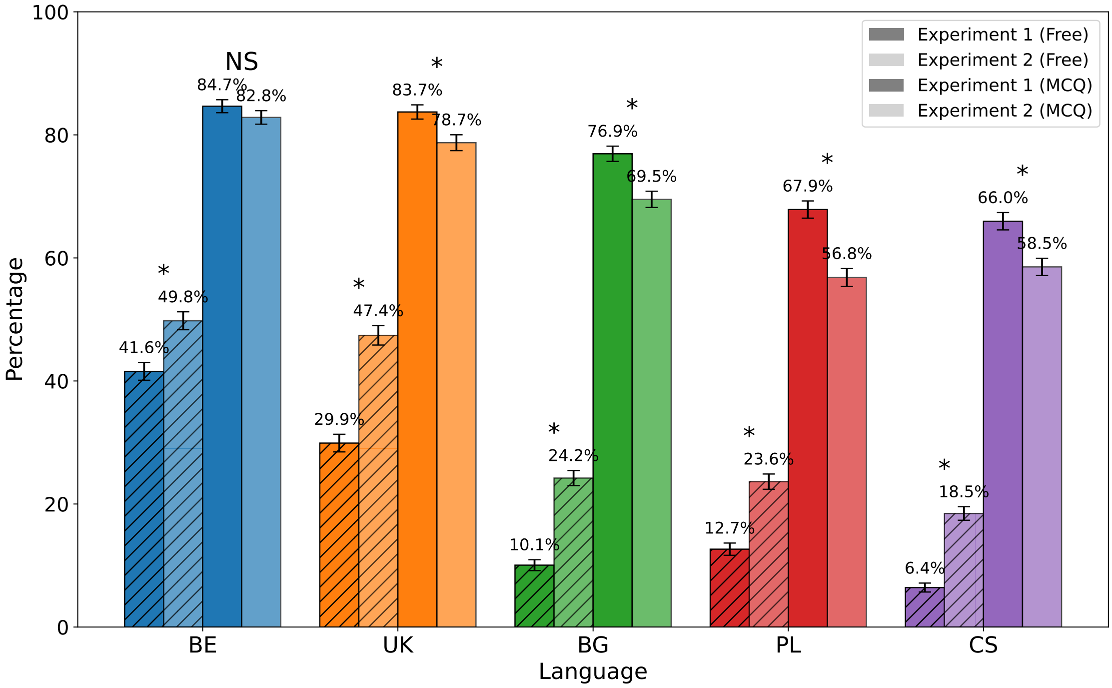
platform for research participant recruitment. Familiarity with the Latin script, which is used by CS and PL languages, was allowed and expected due to the English-language interface of Prolific. All of our participants provided informed consent and were assured to be anonymized in any published data. Participants with any prior knowledge of the target languages were excluded. For Experiment 1 (spoken-only input), we recruited 88 participants (26 males, 60 females, 2 identifying as other genders; age range 21-78 years, mean age 35). For Experiment 2 (spoken and written input), we recruited 118 participants (41 males, 76 females, 1 identifying as another gender; age range 18-59 years, mean age 32). There was also no overlap of participants in the experiment.

2.4 Intelligibility scores and statistical analysis

The percentage of correct responses were considered as the intelligibility scores. For the free translation task, the responses were automatically considered correct if they matched allowed alternative answers in a pre-defined list. For instance, we allowed RU equivalents или что, что ли, или как as possible translations of Ukrainian expression чи що. The responses were further manually checked by a native RU speaker to include correct responses that could have been missed because of typos.

2.4.1 Linguistic distances

To address RQ1 regarding which distances are related to intelligibility, we extracted the orthographic and phonological distances as explained in Section 1 for each test unit differently depending on the task. Specifically, for the free translation task, we used the distance between the original expression and its correct non-compositional translation to RU. For the MCQ task, we used the distance between the correct non-compositional translation to RU and the word-by-word literal translation to RU in order to quantify the gap between an expression's actual meaning and literal interpretation. A larger difference indicates that the true meaning is very different from the literal interpretation. For instance, in the Ukrainian expression все же (literally "everything or", but actually meaning "nonetheless"), we would expect a large difference since the true meaning differs substantially from the literal translation.



Significance levels: * = p < .05, ** = p < .01, *** = p < .001, NS = Non-significant

Figure 2: Intelligibility scores of free translation and MCQ Responses in the two experiments (i.e., Experiment 1 referring to spoken-only inputs while Experiment 2 referring to combined spoken and written inputs). The languages are arranged in descending order by intelligibility scores.

Orthographic distance. We employed Levenshtein Distance which counts the minimum number of single-character operations (i.e., insertions, deletions, and substitutions) needed to transform one word into another (Levenshtein, 1966). It is worth noting that evaluating orthographic distance among Slavic languages is challenging due to their use of two writing systems – Latin and Cyrillic. To address this, we performed ISO 9 transliteration for CS and PL stimuli to convert them to Cyrillic, which is used by the other three target languages and RU. Levenshtein distance has shown potential in analyzing intelligibility. For instance, in Stenger (2019), the authors found the Levenshtein distance of cognates to be a reliable predictor of orthographic intelligibility of Slavic languages that use Cyrillic script. Also, as we mentioned in Section 2.3, our RU participants were not expected to know the correct orthographic pronunciation rules of the target languages, as they had not previously studied these languages. They might use their knowledge of Cyrillic and Latin scripts from exposure to RU and English (Prolific's interface language) to approximate the pronunciation of words written in Latin script.

Phonological distance. We employed Phonologically Weighted Levenshtein Distance (PWLD) which quantifies the distance between different phonemic sequences or word forms (Fontan et al., 2016). This distance extends the string-based Levenshtein Distance by considering the cost of each phoneme substitution based on their phonetic features. We employed the same adaptation of the original PWLD as the one proposed in Abdullah et al. (2021). The phonemic transcriptions for all non-compositional expressions in the target languages and RU were obtained using CharsiuG2P, a transformer-based tool for grapheme-to-phoneme conversion (Zhu et al., 2022).

2.4.2 Surprisal values

In addition to linguistic distances, we extracted surprisal values to address RQ1. We developed a cascaded system that combines automatic speech recognition (ASR) and language modeling. Employing ASR is grounded in psycholinguistic research as ASR errors indicate the second language

Table 1: Mixed-Effects Model with GPT-Large Results

(a) Free translation Task (GPT-Large)

Predictor	Est.	SE	z	p
Main				
Intercept	−1.85	0.32	−5.79	< .001
PWLD	−0.58	0.13	−4.4	< .001
Levenshtein	−0.41	0.14	−2.9	0.004
GPT L	−0.54	0.2	−2.63	0.008
Written	1.23	0.33	3.76	< .001
South	−3.07	0.42	−7.23	< .001
West	−2.48	0.37	−6.79	< .001
2-way				
GL×Wr	0.46	0.14	3.27	.001
GL×S	0.55	0.49	1.12	0.26
GL×W	0.92	0.34	2.7	.007
Wr×S	1.1	0.32	3.47	< .001
Wr×W	0.59	0.26	2.28	.023
3-way				
GL×Wr×S	−1.19	0.37	−3.2	.001
GL×Wr×W	−0.4	0.26	−1.56	0.119

Note. GL = GPT Large, Wr = spoken+written input, S = South, W = West. Random effects variances: Source = 3.25, User = 3.88.

(b) MCQ Task (GPT-Large)

Predictor	Est.	SE	z	p
Main				
Intercept	2.07	0.18	11.45	< .001
PWLD	−0.43	0.08	−5.62	< .001
Levenshtein	−0.33	0.08	−4.15	< .001
GPT L	−0.31	0.13	−2.32	.021
Written	−0.29	0.19	−1.51	.131
South	−0.42	0.23	−1.84	.066
West	−1.05	0.19	−5.41	< .001
2-way				
GL×Wr	−0.03	0.12	−0.25	.805
GL×S	0.58	0.26	2.22	.027
GL×W	0.37	0.19	1.99	.047
Wr×S	−0.3	0.19	−1.57	0.12
Wr×W	−0.2	0.16	−1.25	0.21
3-way				
GL×Wr×S	−0.33	0.22	−1.51	.130
GL×Wr×W	0.09	0.16	0.57	.568

Note. GL = GPT Large, Wr = spoken+written input, S = South, W = West. Random effects variances: Source = 0.96, User = 1.03.

Table 2: Mixed-Effects Model with GPT-Small Results

(a) Free translation Task (GPT-Small)

Predictor	Est.	SE	z	p
Main				
Intercept	−1.81	0.32	−5.7	< .001
PWLD	−0.58	0.13	−4.43	< .001
Levenshtein	−0.41	0.14	−2.9	0.004
GPT S	−0.56	0.20	−2.73	0.006
Written	1.19	0.33	3.67	< .001
South	−3.11	0.42	−7.34	< .001
West	−2.53	0.36	−6.93	< .001
2-way				
GS×Wr	0.46	0.14	3.35	< .001
GS×S	0.57	0.46	1.23	.022
GS×W	1.05	0.35	3	0.003
Wr×S	1.1	0.32	3.49	< .001
Wr×W	0.61	0.26	2.37	0.02
3-way				
GS×Wr×S	−1.07	0.35	−3.06	0.002
GS×Wr×W	−0.37	0.26	−1.4	0.16

Note. GS = GPT Small, Wr = spoken+written input, S = South, W = West. Random effects variances: Source = 3.23, User = 3.88.

(b) MCQ Task (GPT-Small)

Predictor	Est.	SE	z	p
Main				
Intercept	2.10	0.18	11.60	< .001
PWLD	−0.43	0.08	−5.67	< .001
Levenshtein	−0.32	0.08	−4.12	< .001
GPT S	−0.31	0.13	−2.31	.021
Written	−0.29	0.19	−1.50	.135
South	−0.43	0.23	−1.86	.063
West	−1.07	0.19	−5.54	< .001
2-way				
GS×Wr	−0.01	0.12	−0.09	.927
GS×S	0.54	0.24	2.22	.027
GS×W	0.38	0.19	2.01	.044
Wr×S	−0.32	0.19	−1.71	0.08
Wr×W	−0.2	0.16	−1.24	0.21
3-way				
GS×Wr×S	−0.37	0.20	−1.82	.068
GS×Wr×W	0.05	0.16	0.34	.733

Note. GS = GPT Small, Wr = spoken+written input, S = South, W = West. Random effects variances: Source = 0.96, User = 1.03.

learners' listening difficulties (Mirzaei et al., 2016). Also, this two-stage approach aims to model both the acoustic-phonological processing of foreign speech and the subsequent semantic interpretation challenges faced by RU speakers when encountering unfamiliar Slavic languages. The surprisal values provide quantitative insights that can be correlated with human performance on cross-language intelligibility tasks. The cascaded system operates as a two-stage pipeline as described below.

1) Speech-to-Text: First, the Wav2Vec2-Large-Ru-Golos-With-LM model (Bondarenko, 2022) converts speech input from foreign, target Slavic languages into RU text. This ASR component was specifically fine-tuned on the Sberdevices Golos dataset (Karpov et al., 2021), a large-scale RU speech corpus, making it particularly suited for modeling a native RU listener.

2) Surprisal Calculation: The RU text output from the Speech-to-Text stage is fed into two autoregressive models, ruGPT-3-small (125M parameters) and ruGPT-3-large (760M parameters) (Zmitrovich et al., 2024), in order to address RQ2. The ruGPT-3-small and ruGPT-3-large were chosen to represent different model capacities while maintaining domain consistency to address our RQ2. Both models were trained on RU text, making them suitable for modeling native RU speakers' processing. Since these models generate output based solely on left-to-right context, they estimate probabilities for each word in a sequence by conditioning only on prior tokens. The models assign probability scores to each word in the transcribed sequences, and we converted scores into surprisal values by taking the negative log-likelihood of each word. Higher surprisal values indicate that a word or phrase is less predictable within the given context and therefore potentially more difficult to process. For example, in a context like "I like both cats and __ ," the word "dogs" would have a low surprisal score because it aligns with high-probability completions. Conversely, less common or semantically unpredictable sequences would receive higher surprisal values, reflecting greater cognitive processing demands.

2.5 Statistical Analysis

We analyzed the binary response data, i.e., correct vs. incorrect (baseline), using generalized linear mixed-effects models (GLMMs) with a binomial logit link by using *glmer* function in the *lmer* package (Bates, 2016) of R (Team et al., 2013). All continuous predictors (i.e., linguistic distances and surprisal values) were centred to their mean values to reduce collinearity. Experimental factors explained below were dummy-coded. Models were optimized using the bobyqa optimizer (maxfun = 200,000) with Laplace approximation.

For both the free translation and MCQ tasks, the fixed effects were: (1) Linguistic Distances: PWLD and Levenshtein distance, (2) GPT-based Surprisal: Extracted from both large and small GPT models (operationalized as negative log-likelihoods), and (3) Experimental Factors: Experiment input, i.e., spoken-only (Experiment 1) vs. spoken+written (Experiment 2) with spoken-only as the baseline, and Language group (East, South, West Slavic; East as the baseline), including relevant interaction terms.

Random effects comprised intercepts for participants (`user_id`) and source texts (`source_text_to_be_translated`), with random slopes for Experiment input when justified by the data. Model fit was assessed using AIC, and predictor significance was evaluated via z-values and corresponding p-values (with degrees of freedom estimated by Satterthwaite's method where applicable).

3 Results and Discussion

3.1 Intelligibility Scores

Figure 2 shows that intelligibility scores varied both by task and input type. In general, free translation scores were lower than those from the MCQ task, as expected given the greater production demands. While written input improved free translation performance, it adversely affected MCQ responses, suggesting that orthographic cues aid deeper semantic processing but may interfere with rapid, recognition-based decisions. Regarding language groups, East Slavic languages (Belarusian and Ukrainian) demonstrated the highest intelligibility scores, South Slavic (Bulgarian) – intermediate scores, and West Slavic languages (Polish and Czech) – the lowest. This gradient is consistent with prior findings on Slavic intercomprehension (Gooskens and van Heuven, 2021; Stenger and Avgustinova, 2021) and underscores the influence of typological proximity on non-compositional expression processing.

3.2 RQ1: Predictive Power of Linguistic Distances and GPT-based Surprisal

Our analysis revealed distinct patterns in how linguistic distances and GPT-based surprisal predict cross-language intelligibility across tasks. As the results of the free translation task shown in Table 1a, both metrics proved significant predictors: higher the Levenshtein distances (Est. = -0.41, p = 0.004) and higher the surprisal values (Est. = -0.54, p = 0.008), lower the log odds of having a correct response (reflecting lower intelligibility). The MCQ task showed a different pattern (Table 1b). While linguistic distances emerged as the primary predictor (PWLD: Est. = -0.43, $p < .001$; Levenshtein: Est. = -0.33, $p < .001$), GPT-based surprisal had a weaker effect on performance (Est. = -0.31, p = .021). The results with small GPT models in Table 2a and 2b demonstrate the same tendency.

Experiment input and language group also contributed to explaining the intelligibility. As evident in Table 1a, written input improved free translation performance (Est. = 1.23, $p < .001$) but showed no significant contribution for MCQ responses (Table 1b: Est. = -0.29, p = .131). Additionally, compared to East Slavic languages (the baseline level), both South Slavic (Est. = -3.07, $p < .001$) and West Slavic languages (Est. = -2.48, $p < .001$) showed significantly lower intelligibility in the free translation task. Whereas in the MCQ, only West Slavic languages (Est. = -1.05, $p < .001$) stood out.

3.3 RQ2: Comparison of GPT Model Sizes

The results in Tables 1a and 2a for free translation, and in Tables 1b and 2b for MCQ, revealed similar performance patterns of GPT-based surprisal across model sizes in both free translation (Large: Est. = -0.54, p = 0.008; Small: Est. = -0.56, p = 0.006) and MCQ tasks (Large: Est. = -0.31, p = .021; Small: Est. = -0.31, p = .021). These results contradict previous findings claiming that larger model capacity lead to a worse prediction of human performance (Oh and Schuler, 2023a,b). However, the previous studies considered reading times and monolingual experiments. Our results indicate that the role of surprisal in cross-language intelligibility should be treated differently than that in monolingual experiments. On the other hand, the difference in the results could also rise from the fact that we used RU ASR models to generate the input for language model surprisal, which could add more noise to the data.

4 Conclusion

This study investigated (1) how linguistic distances and surprisal derived from GPT models predict cross-language intelligibility of non-compositional expressions (2) and whether GPT-based model size matters for prediction power. The study used free translation and multiple-choice question tasks by giving participants speech-only input or speech+written input. Our results showed that linguistic distances, measured via orthographic and phonological distances, emerged as the strongest predictors of intelligibility in both tasks. GPT-based surprisal was a significant predictor only in the free translation task, highlighting that such a free production task is more sensitive to contextual predictability. Additionally, minimal differences in surprisal's performance between large and small variants suggest that a larger GPT model can predict cross-language comprehension outcomes as effectively as a small one.

These findings underscore the complex interplay between typological proximity, orthographic and phonological similarities, and task demands in shaping cross-language intelligibility. The differential impact of written input across tasks further highlights that while orthography can support deeper semantic processing, it may confound recognition-based tasks. Future research should explore these dynamics in other language families and consider different sizes of language models for predicting cross-language intelligibility.

Ethical statement

Before taking part in the experiments, all the participants gave their consent that their anonymized responses would be used for research purposes. Participants were compensated for their work in standard rate suggested by Prolific.

Limitations

While our study provides valuable insights into the cognitive mechanisms underlying cross-language intelligibility, it is based on native Russian speakers and specific ASR and language models for Russian. Further work is needed to generalize these findings to other language groups. Additionally, the gender imbalance among recorded speakers may have influenced results and should be addressed in future studies.

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A Microsyntactic Units in six Slavic languages used as Experimental Stimuli

Type	BE	UK	BG	CS	PL	RU
Prep	ў канцы	у кінці	в края на	na konec	w końcu	в конце
Eng. trans.	*at the end of*	*at the end of*	*at the end of*	*at the end of*	*at the end of*	*at the end of*
Adv & Pred	не раз	не раз	не веднъж	ne jednou	niejednokrotnie	не раз
Eng. trans.	*not once*	*not once*	*not once*	*not once*	*not once*	*not once*
Parenth	такім чынам	таким чином	такъв начин	tímto způsobem	w taki oto sposób	таким образом
Eng. trans.	*in this way*	*in this way*	*in this way*	*in this way*	*in this way*	*in this way*
Conj	хіба толькі	хіба що	освен да	snad jen	chyba że	разве что
Eng. trans.	*except (only) that*	*except (only) that*	*except (only) that*	*except (only) that*	*except (only) that*	*except (only) that*
Part	усе ж	все же	все пак	asi spíš	więc jednak	все же
Eng. trans.	*nonetheless*	*nonetheless*	*nonetheless*	*nonetheless*	*nonetheless*	*nonetheless*

Note: We use ISO 639-1 codes for the languages: Belarusian (BE), Ukrainian (UK), Bulgarian (BG), Czech (CS), Polish (PL), Russian (RU).

Table 3: Microsyntactic units in six Slavic languages.