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DO UNHAPPY REVIEWERS MIX IN MORE RUSSIAN? STAR RATINGS AND KAZAKH-RUSSIAN CODE-SWITCHING IN 175,002 ONLINE REVIEWS

Abstract: Bilingual people often say that they switch languages when they are emotional, but no measurement of this for Kazakh and Russian was found. This study asks whether Kazakh-speaking reviewers mix Russian words into their reviews more often when they are dissatisfied (1-2 stars) than when they are satisfied (4-5 stars). The data are all 175,002 non-empty reviews of the public KazSAnDRA dataset of Kazakh online reviews, each with a star rating from 1 to 5. For every review, the share of Russian words among all words was counted with an automatic rule that the author's mentoring team built from a boundary and twenty example words she wrote before the count: an old, established loanword such as *телефон* or *автобус* counts as Kazakh, while a Russian word used instead of an existing Kazakh one, such as *скидка* or *доставка*, counts as Russian. A word-by-word check of all 1,763 words in 160 randomly drawn reviews (60 of them drawn from reviews the rule marked as mixed), made by an AI assistant, found 90% precision and 83% recall (92% and 83% in the fully random part). The mean share of Russian words falls with the rating, from 3.85% in 1-star reviews to 2.49% in 5-star reviews (ratio 1.55, 95% CI 1.50 to 1.60), and 1-2-star reviews contain 1.49 times as much Russian as 4-5-star reviews. The direction predicted by the author's hypothesis is confirmed, but her forecast of "three times" was about twice the observed ratio. The difference comes almost entirely from how often a review contains any Russian (23.5% of 1-star against 15.5% of 5-star reviews); among reviews that do, the share of Russian words is only slightly higher (1.05 times in short and 1.18 times in long reviews). The difference holds in every additional check (smallest ratio 1.17, at 10 per million) and is larger in long reviews (1.79 times) than in short ones (1.43). Relative to their frequency, the largest excess (3.15 times; a grouping made after a first review) is in Russian emphatic particles and degree adverbs such as *вообще*, *уже*, *еще* and *даже*; they are about a tenth of the extra Russian words, most of which are content words such as *реклама* and *обновление*.

Keywords: code-switching; Kazakh-Russian bilingualism; emotion; sentiment; online reviews; star ratings; corpus linguistics; KazSAnDRA.

1. Introduction

In Kazakhstan many people use two languages, Kazakh and Russian, and move between them inside one conversation or even one sentence. The author's first study looked at how this mixing is built: in 2,447 Kazakh sentences with Russian words from online reviews, almost every switch was a single Russian word inserted into a sentence whose grammar stayed Kazakh [1]. That study answered the question of how people mix. It did not ask when they mix.

One common answer to "when" is "when we are emotional": the author's own observation, written before the count (Section 3), was that people switch to Russian to express criticism, and code-switching is described as a strategy for expressing emotion [8]. Kazakh and

Russian are the two main languages of Kazakhstan, and how each of them is used has been studied for years [2], but no test of the link between emotion and mixing on real written Kazakh was found. The online reviews used in the first study offer a chance to make one, because every review in the KazSAnDRA dataset carries a rating from 1 to 5 stars, which the dataset's creators describe as a measurable representation of the reviewers' attitudes [3]. The rating is therefore a direct signal of how satisfied the writer was.

This paper therefore asks one narrow question: do people mix Russian into Kazakh more often in dissatisfied reviews (1-2 stars) than in satisfied reviews (4-5 stars)? It uses all 175,002 non-empty reviews of the public dataset and measures mixing as the share of Russian words in each review. The author's hypothesis and a numerical forecast were written down before any count was made.

2. Background

2.1 Language choice and emotion in bilinguals

Research on bilingualism shows that the two languages of a bilingual person do not carry the same emotional weight. In a survey of 1,039 multilinguals, swearwords and taboo words felt most powerful in the first language [4]. In about 430,000 tweets of Hindi-English bilinguals, Hindi, the native language, was preferred for negative opinions and swearing [5]. But in a Spanish/Galician conversation, indignation was expressed in Spanish, the dominant language, and contempt in Galician, the less dominant one [6]. Switching languages was also tied to emotion and emotional labour for 15 Iranian English teachers in class [7], and a review in this journal describes code-switching as one of the strategies bilinguals use to express emotion [8]. Because the direction differs between pairs, it has to be measured for each pair.

2.2 Measuring emotion in mixed-language text

Large-scale work on emotion in mixed text comes mostly from computational linguistics, where annotators decide the emotion of each text. Lee and Wang annotated Chinese-English posts from the social network Weibo for the emotion each language expresses and found English used more for happiness than for sadness [9], and Tang and colleagues fine-tuned BERT classifiers to detect several emotions at once in Chinese-English text [10]. Annotators often disagree: in the English-Spanish EN-ES-CS corpus of Vilares and colleagues, Krippendorff's alpha was 0.629 to 0.664 for negative and 0.500 to 0.693 for positive sentiment [11]. Star ratings avoid this problem because the writer gives the rating, but ratings on review platforms usually form a "J-shaped" distribution, with many 5-star ratings, some 1-star ratings and few in between [12]; KazSAnDRA has this shape, with 131,021 of its 180,064 reviews at 5 stars [3].

2.3 The gap

Three papers in this journal discuss emotion or language mixing without counting it in texts: a review of emotional expression in two languages [8], a description of youth slang and language mixing on social networks [13] and a survey-based study of language, psyche and society [14]. Kazakh-Russian code-switching was counted in real reviews in the author's first study [1] and tested on language models in a benchmark [15], but neither uses an emotion signal. The present study joins the two lines.

3. Hypothesis and forecast

The research question was fixed on 17 September 2026. The next day, before any count, the author wrote the hypothesis (her texts are edited for grammar and spelling; words added or replaced for meaning are in square brackets):

"I hypothesize that there would be more Russian words in negative reviews [rated] 1-2 than in positive reviews [rated] 4-5. Perhaps people switch to Russian language in negative

feedback in order to emphasize their dissatisfaction or highlight the issue emotionally. In positive comments, on the other hand, language can stay more plain since the author does not need to emphasize emotions that intensively. Therefore, I anticipate more frequent Kazakh-Russian language mixing in negative comments specifically."

On 4 October 2026, again before any count, she added the reason for her forecast:

"I suppose that there would be more Russian words in reviews with 1-2 stars specifically. According to my observations, people tend to switch to Russian in cases when they want to express their criticism or dissatisfaction. Kazakh language, on the other hand, is used in a laconic style when the person is satisfied. The reason for this difference lies in the fact that Russian has a more extensive critical vocabulary, which is needed for expressing discontent. In Kazakh, thank-you lexis prevails."

Asked on 5 October how many times higher the share of Russian words in 1-2-star reviews would be than in 5-star reviews, with "one and a half or three times" given as examples in the question, she answered: three times. This is the forecast checked in Section 6.2. The analysis plan (Section 5.4) was written by her mentor and approved by the author on 6 October 2026, also before any share was computed.

4. Data

4.1 The KazSAnDRA dataset

On 2 October 2026 the author summarised the dataset paper [3]: the reviews come from four sources, namely an app store for Android devices (Appstore), an online library of Kazakh books and audiobooks (Bookstore), map and navigation services (Mapping) and online marketplaces (Market); 180,064 reviews were collected, of which 25,235 have one star, 4,929 two, 7,262 three, 11,617 four and 131,021 five; and the dataset is released under the CC BY 4.0 licence.

According to the dataset paper, the reviews were collected between September 2022 and September 2023, checked by native speakers of Kazakh and left as written [3], so they keep their misspellings, Kazakh typed in Russian letters, Latin script and Russian words; the release keeps this original text (column text) next to the lower-cased copy without punctuation and emoji (text_cleaned) that the dataset paper describes as its pre-processing [3, 16], and only the original text is used here.

4.2 Which reviews were used

The dataset paper reports 180,064 collected reviews [3]. Before publishing, its creators removed duplicates (identical text and score) [16]; the public release contains 175,158 reviews with their original 1-5 scores (the three "score classification" files: 140,126 training, 17,516 validation and 17,516 test reviews) and 173,374 distinct review texts. The author's first study reported 172,015 reviews [1]. A recount made for this paper shows that 172,015 is exactly the number of distinct review texts in the polarity files plus the score-classification training file, that is, without the score-classification validation and test files, so the first study most likely scanned about 99% of the distinct review texts. This paper uses the complete release: 175,158 reviews, of which 156 contain no words at all (only emoji, digits or punctuation), leaving 175,002 reviews with 1,507,052 words.

4.3 Why star ratings, and their weak points

The author explained the choice of star ratings as follows (24 September 2026):

"The usage of authors' ratings (on a scale from 1 to 5 stars) as a metric of the emotional sentiment of the review has a principal advantage in comparison with traditional expert annotation, since the author's rating measures emotions more faithfully and more accurately

than ratings assigned by external annotators. In conventional corpora (for example, the EN-ES-CS Corpus) the sentiment annotations of external experts demonstrate a low level of agreement (inter-annotator agreement), as people rate someone else's anger or approval, filtering the text through their own perception. Ratings provided by the authors themselves reflect their authentic internal state during writing. The author is not trying to 'guess' the emotion: they show it, [which] eliminates the misrepresentations inevitable in external interpretations of textual markers. Nonetheless, this approach has its own weaknesses that have to be considered in the analysis. Scale subjectivity: for one user, deep disappointment (high level sentiment) is expressed as 1 star, while the other one puts 3 stars with [a similar] anger level ('it could be worse'). Cognitive shift: users tend to write reviews in an 'affect', that is, emotional excitement. For this reason, the selection naturally shifts to polar values (1 or 5 stars), diluting the neutral zone. Textual discrepancy: a star rating measures the overall impression of an experience, whereas the review itself may contain complex code-switching, sarcasm or a detailed description of specific advantages and disadvantages, which formally contradict the overall rating."

The agreement measured there was low to moderate [11]. This study treats the stars as a measure of satisfaction rather than of emotion as such (Section 8).

These weak points are visible in the data. Only 7,184 of the 175,002 reviews (4.1%) have 3 stars, while 126,525 (72.3%) have 5 stars. For this reason the study compares shares inside each rating group, never raw numbers of Russian words, and it reports the planned comparison of 1-2 against 4-5 stars together with the comparison of the two extremes, 1 against 5 stars.

5. Method

All counts and statistics in this paper were computed in Python by the author's mentoring team with an AI assistant (see the contributions note at the end).

5.1 What counts as a word

A word is a run of letters (Cyrillic or Latin; parts joined by a hyphen are kept together) in the original review text, written in lower case. Digits, emoji and punctuation are not words. By this definition the median review has 6 words and the mean review 8.6 words.

5.2 What counts as a Russian word

Many Russian-origin words have been part of Kazakh for decades, so "Russian origin" cannot be the test. The boundary used here is the author's own, written on 27 September 2026, before the count:

"I would draw a line depending not on the word origin, but on the perception of this word as common in Kazakh speech. If the word has been used in Kazakh for a long time, has a usual form, and appears in daily speech without feeling like a switch, I would not count it as code-switching. If the word looks like Russian but is used instead of a Kazakh one, I count it as a Russian insertion. For example, I do not consider these words as a [switch]: «Телефон», «Машина», «Магазин», «Компьютер», «Автобус», «Завод», «Банк», «Билет», «Паспорт», «Телевизор». These words, on the other hand, are Russian insertions for me: «Скидка», «Доставка», «Заказала», «Понравилось», «Качество», «Обслуживание», «Удобно», «Дорого», «Продавец», «Размер». This line is needed to count cases of switching to Russian specifically, but not the words that are normally used in Kazakh."

There are 141,940 different words in the reviews, too many to judge one by one, so the mentoring team turned the rule into steps that a computer applies to every word:

1. A word in Latin letters is not Russian.

2. The author's ten Kazakh words above, with or without Kazakh endings (*телефонды, банкке*), are not Russian; her ten Russian words are Russian.

3. Russian function words that have no common Kazakh twin (*и, в, с, что, это, очень, уже* and similar; the list was drawn up by the AI assistant) are Russian; two of them, *я* and *о*, can also be Kazakh particles and make up 1.3% of the Russian words counted. Words that exist in both languages, such as *да* and *не* (Kazakh "too" and "what"), *он* (Kazakh "ten") or *а*, are not counted as Russian.

4. A Russian stem with Kazakh endings (*приложение-ге, доставка-сы, курьер-ге*) is counted as a Russian word, because the word itself is Russian and is used instead of a Kazakh one (*қолданба, жеткізу*); only its ending is Kazakh. Such words make up 17.5% of all Russian words found. This is more than the 4.9% of single-word switches with Kazakh endings in the first study [1]; the two figures come from different counting rules and units and are not directly comparable.

5. Any other word is Russian if it is in the Russian dictionary of the morphological analyser pymorphy3 (based on pymorphy2 [17]; proper names excluded) and it is not established in Kazakh. "Established" is measured in edited Kazakh text: the word and its Kazakh-suffixed forms must occur at least 1.75 times per million words in Kazakh Wikipedia [18] (22.2 million words, counting only clearly Kazakh sentences), also when Kazakh letters are typed as Russian ones (*көн* typed as *кон*).

The threshold of 1.75 per million was set from the author's twenty words. In Kazakh Wikipedia, her ten "Russian" words occur at most 1.62 times per million (*размер*), and her ten "Kazakh" words at least 1.85 times per million (*магазин*, one of the four examples her mentor gave when he asked for the list); any threshold between the two reproduces all twenty of her decisions. Finally, the AI assistant reviewed the 300 most frequent words that the steps marked Russian and the 150 most frequent mixed words, reading uncertain ones in context, and made 46 corrections: 18 Kazakh words typed in an unusual way (for example *дым* "nothing at all", *кермет* for *керемет*), 27 names and interjections (for example the brand *Флин* and *вау*) and one Kazakh particle (*ко*). These corrections were made on word frequencies over all reviews, without looking at the star ratings.

Table 1 shows the rule on two reviews drawn at random from the data (one 5-star and one 1-2-star review of 8 to 30 words containing at least one Russian word, without obscene words).

Table 1. The counting rule on two randomly drawn reviews

Review (stars)	Words	Russian words	Share
«Өте керемет еш минус жоқ мен сол себеппен 5 звёзд қойып отырм» (5)	11	1 (звёзд)	9.1%
«Қазақ тілі жоқ. Қазақ тілді қауымның құқығын шектеп тұрсыз! Нету казахского языка» (1)	12	3 (нету, казахского, языка)	25.0%

The rule does not count *минус* (1.85 per million in Kazakh Wikipedia, just above the threshold); the check in Section 5.5 judged a use of *минус* in place of Kazakh *кемшілік* to be

Russian, so words like this are among the rule's misses. *Звезд* is a Russian case form. The second review is a complaint that an application has no Kazakh language, written first in Kazakh and then repeated in Russian.

5.3 The measure: the share of Russian words

For each review the measure is the number of Russian words divided by the number of all words. Her mentor set out two options, a simple "yes or no" and the share, with the example of a 100-word and a 10-word review; the author chose the share over the other option her mentor offered and explained why (25 September 2026):

"For every review I count the proportion of Russian words among all words. I think this method is more accurate because it shows not only the presence of [mixing], but also how conspicuous it is in the commentary itself. For example, two Russian words in a 100-word review and one Russian word in a 10-word review are not the same thing, although with 'yes or no' both reviews would simply be considered mixed. Therefore, the 'yes/no' option is too harsh: it does not take into account the length of the feedback and the number of Russian words. The percentage allows [us] to compare reviews of different sizes and see the real degree of mixing."

The "yes or no" measure is still reported as a check (Section 6.4).

5.4 The planned comparisons

The plan approved on 6 October 2026 was: (1) compute the share of Russian words in every review and the mean share for each rating; (2) compare 1 against 5 stars and 1-2 against 4-5 stars, comparing shares, not numbers of words, because the groups differ in size; (3) repeat the comparison separately for short reviews (10 words or fewer) and long reviews (more than 10 words), so that a difference cannot simply be a difference in length. The forecast is checked by the ratio of the mean share in 1-2-star reviews to the mean share in 5-star reviews.

For each comparison the paper reports the two mean shares, their difference and their ratio with 95% bootstrap confidence intervals (2,000 resamples of reviews within each group), the p-value of the Mann-Whitney U test, and the rank-biserial correlation as an effect size (0 means no difference, 1 means every review of one group is above every review of the other). The confidence intervals of single means (Table 2, Figure 1) use the normal approximation. With groups of tens of thousands of reviews even tiny differences have tiny p-values, so the paper relies on the size of the difference.

Checks added after the plan are reported as such: domains; the "yes or no" measure; a context version of the rule, in which a shared word (such as *не*) counts as Russian when the nearest non-shared word on each side, where one exists, is Russian; only reviews with a Kazakh-specific letter; thresholds of 1, 2.5, 5 and 10 per million; texts that occur once; and, after a first review of this paper, the share among mixed reviews, the classes of Table 5 and runs of Russian words.

5.5 Word-by-word check of the rule

The rule was checked on two random samples, with the star ratings hidden: 100 reviews drawn from all reviews with at least 3 words (913 words), and 60 reviews drawn from the reviews in which the rule found at least one Russian word (850 words). Each word was read against the author's boundary in Section 5.2. The reading was done by the same AI assistant that wrote the code, so it is a second application of the boundary, not an independent human judgement. Loanwords under 2.5 per million in Kazakh Wikipedia (the next threshold tested), here *минус*, *пароль*, *реанимация* and *ресторан*, were judged Russian when used in place of a Kazakh word (*кемілік*, *құпиясөз*, *жансақтау*, *мейрамхана*), and a shared word such as *a* or *не* was judged Russian inside a Russian phrase. Over the 1,763 words, the rule agreed with the

reading on 98.0% of words. Of the words the rule marked Russian, 89.9% were Russian (precision), and it found 83.5% of the Russian words (recall). In the fully random sample the figures were 92.1% and 83.3%. The missed words were mostly misspelt Russian words (*саглаиуись, снаубо*) and slang, and the false alarms were mostly names and Kazakh endings typed apart from their word (*мб ты*). When the ratings were joined after the reading, the errors were not tied to the rating: in 1-2-star reviews precision was 0.94 and recall 0.87, in 4-5-star reviews 0.85 and 0.79, and in both groups the rule counted 0.93 times as many Russian words as the reading.

6. Results

6.1 Russian words by rating

Across all 175,002 reviews, 47,028 of 1,507,052 words (3.1%) are Russian, and 17.3% of reviews contain at least one Russian word. Reviews written wholly in Russian are almost absent (50 reviews), as expected in a dataset collected as reviews in Kazakh [3]; the Russian words appear inside Kazakh reviews, as in the first study [1].

Table 2. Russian words by star rating

Stars	Reviews	Words	Russian words	Reviews with any Russian, %	Mean share, % (95% CI)
1	25,019	232,629	10,795	23.5	3.85 (3.74 to 3.97)
2	4,896	44,644	1,756	21.1	3.50 (3.24 to 3.75)
3	7,184	67,842	2,654	21.8	3.58 (3.38 to 3.78)
4	11,378	102,838	3,453	19.5	3.09 (2.94 to 3.24)
5	126,525	1,059,099	28,370	15.5	2.49 (2.45 to 2.53)

The share of Russian words is highest in 1-star reviews and lowest in 5-star reviews, and it falls almost step by step in between (Table 2, Figure 1a); only 2 and 3 stars are in reverse order, and their confidence intervals overlap.

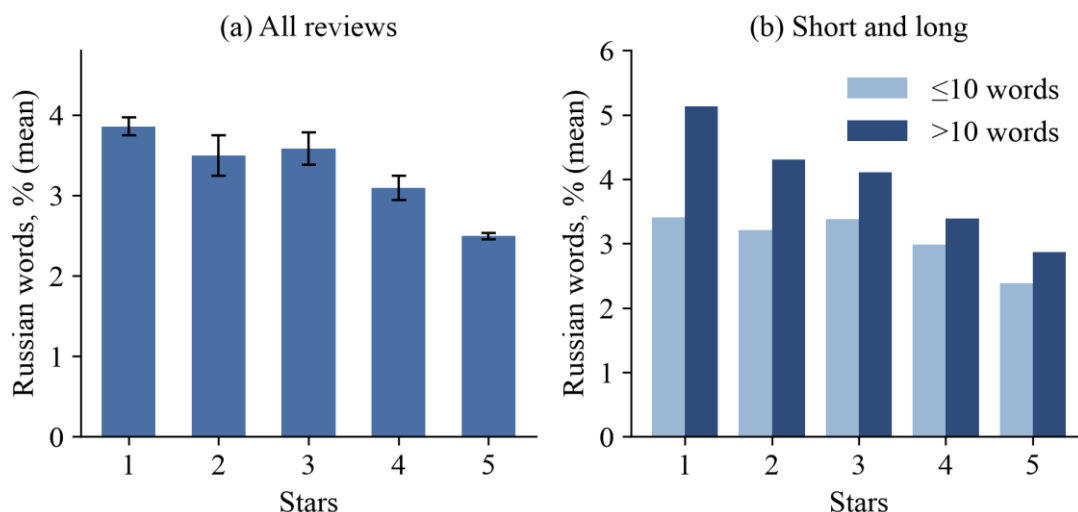


Figure 1. Mean share of Russian words by star rating: (a) all reviews, with 95% confidence intervals; (b) short reviews (10 words or fewer) and long reviews (more than 10 words)

6.2 The planned comparisons and the forecast

Table 3. Planned comparisons of the mean share of Russian words

Comparison	Reviews	Mean share, %	Difference, percentage points (95% CI)	Ratio (95% CI)	Rank-biserial r
1 vs 5 stars	25,019 vs 126,525	3.85 vs 2.49	1.36 (1.25 to 1.48)	1.55 (1.50 to 1.60)	0.08
1-2 vs 4-5 stars	29,915 vs 137,903	3.80 vs 2.54	1.25 (1.14 to 1.36)	1.49 (1.45 to 1.54)	0.07
1-2 vs 5 stars (forecast)	29,915 vs 126,525	3.80 vs 2.49	1.30 (1.19 to 1.42)	1.52 (1.47 to 1.57)	0.08

All three differences are in the direction of the hypothesis, with Mann-Whitney $p < 0.001$. Dissatisfied reviews contain about one and a half times as much Russian as satisfied reviews. The forecast was three times: the observed ratio for 1-2 against 5 stars is 1.52, and the whole confidence interval (1.47 to 1.57) lies far below 3, so the forecast was about twice the observed ratio. The hypothesis is supported in direction, not in size.

The effect is small in the sense of the rank-biserial correlation (0.07 to 0.08), because most reviews in every group contain no Russian at all. The difference comes almost entirely from how often a review contains any Russian (23.5% of 1-star reviews against 15.5% of 5-star reviews). Among the 30,249 reviews that do contain Russian, the mean share of Russian words is almost the same: 16.41% for 1 star against 16.12% for 5 stars (ratio 1.02, 95% CI 1.00 to 1.04), and 16.44% for 1-2 stars against 16.10% for 4-5 stars (ratio 1.02, 95% CI 1.00 to 1.04). It is higher in both length groups (1 against 5 stars, long: 1.18, 95% CI 1.15 to 1.22; short: 1.05, 1.02 to 1.07); the overall ratio is near 1 because mixed 1-star reviews are more often long (53.7% against 45.5%), and long reviews have lower shares (9.5% against 22.4% in short mixed reviews).

6.3 The length check

Short reviews (10 words or fewer) make up 76.7% of the data (134,289 reviews). The difference holds in both length groups (Figure 1b): in short reviews the share is 3.40% for 1 star against 2.39% for 5 stars (ratio 1.43, 95% CI 1.36 to 1.50), and in long reviews it is 5.13% against 2.87% (ratio 1.79, 95% CI 1.72 to 1.87). For 1-2 against 4-5 stars, the ratios are 1.39 (1.33 to 1.45) for short and 1.71 (1.64 to 1.78) for long reviews. The difference is not produced by length; it is larger in long reviews, perhaps because the writer has room to explain the problem (not tested).

6.4 Additional checks

Table 4. Additional checks (not in the plan): ratio of mean shares (95% CI)

Check	1 vs 5 stars	1-2 vs 4-5 stars
Main result (Table 3)	1.55 (1.50 to 1.60)	1.49 (1.45 to 1.54)
"Yes or no" measure (reviews with any Russian)	1.52 (1.48 to 1.56)	1.46 (1.43 to 1.50)
Context version of the rule	1.55 (1.50 to 1.61)	1.50 (1.45 to 1.55)
Only reviews with a Kazakh-specific letter (141,470)	1.49 (1.43 to 1.54)	1.44 (1.39 to 1.49)
Only texts that occur once (170,846)	1.58 (1.53 to 1.63)	1.53 (1.48 to 1.58)
Threshold 1 per million	1.57 (1.52 to 1.63)	1.52 (1.47 to 1.56)
Threshold 2.5 per million	1.55 (1.50 to 1.60)	1.49 (1.45 to 1.54)
Threshold 5 per million	1.32 (1.28 to 1.36)	1.29 (1.26 to 1.33)
Threshold 10 per million	1.19 (1.16 to 1.23)	1.17 (1.14 to 1.21)
Appstore only (132,417)	1.49 (1.44 to 1.55)	1.43 (1.39 to 1.48)
Market only (29,097)	1.45 (1.22 to 1.70)	1.40 (1.21 to 1.61)
Mapping only (8,492)	1.96 (1.73 to 2.20)	1.92 (1.71 to 2.16)
Bookstore only (4,996)	2.07 (1.31 to 3.04)	1.92 (1.28 to 2.73)

Dissatisfied reviews contain more Russian in every check (Table 4); the smallest ratios are 1.19 (1 against 5 stars) and 1.17 (1-2 against 4-5 stars), both at 10 per million. The "yes or no" measure gives almost the same ratio as the share, in line with Section 6.2. The ratio shrinks at high thresholds because common Kazakh words that are also Russian dictionary forms start to count as Russian, above all *разы* (as in *Алла разы болсын*, "may God be pleased"; 5,085 uses, 98.6% outside 1-2-star reviews); at 10 per million the rule also adds *цунер* (2,052 uses, 97.2% outside 1-2-star reviews), a praise word that her boundary could count as Russian, while *пароль* (329 uses, 69.0% in 1-2-star reviews) works the other way. These thresholds therefore partly break the author's boundary, which is why the threshold was set from her twenty words.

6.5 Which Russian words make the difference

Table 5. Russian words per 100 words in 1-2-star and 5-star reviews (each word in one class only; all words of each group counted together, so the last row differs from the mean shares in Table 3; bootstrap intervals from 1,000 resamples of reviews). The first row, a grouping made after a first review, counts вообще, уже, ещё/еще, даже, очень, просто, только, тоже, также, ведь, же, ну, вот, уж, лишь and ни

Type of Russian word	1-2 stars	5 stars	Ratio (95% CI)
Emphatic particles and degree adverbs (16 words, see the note)	0.25	0.08	3.15 (2.82 to 3.53)
Other function words (и, но, на, в, что, это)	0.63	0.39	1.63 (1.51 to 1.78)
Russian stem with Kazakh ending (приложение-ге)	0.75	0.46	1.61 (1.52 to 1.70)
Other Russian content words (приложение, реклама)	2.90	1.75	1.66 (1.60 to 1.72)
All Russian words	4.53	2.68	1.69 (1.64 to 1.75)

The largest ratio is for Russian emphatic particles and degree adverbs (Table 5). Per 10,000 words, *вообще* occurs 6.46 times in 1-2-star reviews against 0.51 times in 5-star reviews, *уже* 5.77 against 1.28, *еще* 4.54 against 1.01 and *даже* 2.16 against 0.59, while the conjunctions *и* (10.39 against 6.54) and *но* (4.69 against 3.59) and the preposition *на* (2.16 against 2.04) differ much less. These words carry no topic of their own and are often used for emphasis (*вообще*, *даже*), although *уже* and *еще* can also mark time ("already", "still, again"); how each was used was not checked. In absolute terms, 1-2-star reviews contain 1.85 more Russian words per 100 words than 5-star reviews: the particles account for 0.17 of them (9%), other function words for 0.24 (13%), mixed words for 0.28 (15%) and other content words for 1.15 (62%), such as *реклама* (10.10 against 1.91 per 10,000 words) and *обновление* (5.12 against 0.73). Russian words also stand somewhat more often next to another Russian word in dissatisfied reviews: 25.0% of the Russian words in 1-2-star reviews are in runs of two or more Russian words, against 20.2% in 5-star reviews (difference 4.8 percentage points, 95% CI 3.1 to 6.7). The Kazakh word of thanks *рахмет* / *рақмет* occurs 129.8 times per 10,000 words in 5-star reviews and 10.5 times in 1-2-star reviews.

7. Discussion

The main result supports the author's hypothesis in direction: the more dissatisfied the writer, the larger the share of Russian words in a Kazakh review. The share falls almost step by step across the ratings and the difference holds in every check of Table 4, but the forecast of three times was too high: the observed ratio is about one and a half. The difference lies mainly in whether a dissatisfied writer uses any Russian at all; once a review mixes, the share of Russian words is only slightly higher, most in long reviews.

The reasons the author gave before the count can now be compared with the data. Her remark that thanks prevail in satisfied Kazakh reviews is clearly supported: *рахмет* is more than twelve times as frequent in 5-star reviews as in 1-2-star reviews, while Russian *спасибо* occurs 0.7 times per 10,000 words in 5-star reviews. Her idea that Russian supplies the words for discontent is supported in part. In absolute terms most of the extra Russian words are content words, many of them technical nouns for the things people complain about (*реклама*, *обновление*, *логин*, *заказ*), which may be Russian because the technology is often named in Russian, not because the writer is angry. But relative to how often they occur, the largest excess

is in Russian emphatic particles (*вообще, уже, еще, даже*), which carry no topic of their own and fit her reason for the hypothesis, that people switch to Russian "to emphasize their dissatisfaction". This study cannot fully separate emotion from topic (Section 8).

The direction connects to Section 2.1: negative opinion moved towards the native language in Hindi-English tweets [5] and contempt towards the less dominant language in a Spanish/Galician conversation [6]; here it moves towards Russian, but the writers' first language is unknown, so the result does not decide between these two pictures.

The result also adds to the author's first study, which found that Russian usually enters a Kazakh sentence as one bare word [1]. In dissatisfied reviews Russian words stand somewhat more often in multi-word Russian stretches (25.0% of Russian words against 20.2%), so single-word insertion remains the usual form of mixing in both groups, with longer Russian stretches a little more frequent when the writer is unhappy.

8. Limitations

First, the automatic rule agreed with a word-by-word reading on 98% of words (90% precision, 83% recall), and that reading was made by the AI assistant that wrote the code, not by a human reader. Second, "established in Kazakh" was measured by Kazakh Wikipedia, which is formal written Kazakh; everyday loanwords that Wikipedia uses rarely, such as *магазин*, are kept as Kazakh only because the threshold was set just below *магазин* (1.85 per million). Third, the star rating measures satisfaction with a product or service rather than emotion as such (Section 4.3). Fourth, the topic of a review is mixed with its rating: complaints are often about technical problems with Russian names. Fifth, three quarters of the reviews are about mobile applications, and nothing is known about the writers. Sixth, KazSAnDRA was collected as reviews in Kazakh [3], so a review written only in Russian is almost invisible here; the true difference may be larger. Seventh, the bootstrap treats reviews as independent, although the dataset paper reports, for the app-store reviews alone, 47,887 named users and 1,759 applications [3]; reviews by the same person or about the same application are alike, so the confidence intervals are too narrow. Finally, this is an observational study: it shows that dissatisfaction and Russian go together, not that dissatisfaction causes the switch.

9. Conclusion

In 175,002 Kazakh online reviews, dissatisfied writers mixed in about one and a half times as much Russian as satisfied writers: Russian words made up an average of 3.85% of the words of a 1-star review against 2.49% of a 5-star review. The author's prediction of the direction was right; her forecast of three times was about twice the observed ratio. The difference comes mainly from how often a review contains any Russian and is larger in long reviews than in short ones; relative to how often they occur, it is largest for Russian emphatic particles such as *вообще* and *уже* (3.15 times), although most of the extra Russian words are content words. A next step would be to separate emotion from topic, for example by comparing reviews of the same application that differ only in rating, or by using a second emotion signal next to the stars.

Data availability. KazSAnDRA is freely available under CC BY 4.0 [3] from its repository [16]. The analysis code, the word lists, the Kazakh Wikipedia frequency list and the per-review counts are kept by the author's research mentor and are available on request.

Author contributions and use of AI tools. Saida Komekova shortlisted two of five research directions prepared by her mentor and agreed to the one he recommended; wrote the hypothesis (18 September 2026) and the reasons for her forecast (4 October), and chose its size, three times, from the two examples in her mentor's question of 5 October (one and a half or

three); chose the share of Russian words over a yes/no measure, the two options her mentor set out, and explained why (25 September; the 100-word and 10-word example came from her mentor's question); drew the boundary between Russian insertions and established loanwords and wrote the two lists of ten words that set the counting rule (27 September; four of her ten Kazakh examples, телефон, магазин, машина and компьютер, were the examples given in her mentor's question of 25 September); found five of the studies cited in Section 2 [6, 7, 9, 10, 11] and wrote a one-line summary of each; wrote the paragraph on star ratings (24 September); summarised the dataset paper (2 October); and approved the analysis plan (6 October). Her paragraphs are quoted in Sections 3, 4.3, 5.2 and 5.3, edited for grammar and spelling, with words added or replaced for meaning in square brackets. Her mentor proposed the five directions, fixed the wording of the question, chose the journal and the three comparison papers from it, and wrote the analysis plan. An AI assistant (Claude, Anthropic), working for her mentor, wrote and ran all of the code (downloading the data, the Kazakh Wikipedia frequency list, applying the counting rule to every word, the recount of the dataset in Section 4.2, the statistics and the figure), drew up the list of Russian function words, grouped the Russian words into the classes of Table 5, made the 46 word corrections and the word-by-word check described in Sections 5.2 and 5.5, found and checked the other references, and drafted the rest of the English text around the author's paragraphs. Apart from the AI assistant's word decisions in Section 5.2 (the 46 corrections and the list of Russian function words), its grouping of 16 words as emphatic particles and degree adverbs in Table 5 and its word judgements in Section 5.5, no number in this paper comes from a language model: every number comes from running the code on the public data, and every reference was opened and checked against its source. K.S. Dyussembina agreed to act as scientific supervisor.

Conflict of interest. The author declares no conflict of interest.

References:

1. Komekova S. Testing classic code-switching constraints on Kazakh-Russian social-media text: an insertional corpus study // *Central Asian Scientific Journal*. 2026. No. 2(30), Vol. 3. P. 50-58.
2. Smagulova J. Language policies of Kazakhization and their influence on language attitudes and use // *International Journal of Bilingual Education and Bilingualism*. 2008. Vol. 11, No. 3-4. P. 440-475. DOI: 10.1080/13670050802148798.
3. Yeshpanov R., Varol H.A. KazSAnDRA: Kazakh Sentiment Analysis Dataset of Reviews and Attitudes // *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*. Torino: ELRA and ICCL, 2024. P. 9657-9667. URL: <https://aclanthology.org/2024.lrec-main.844/> (accessed: 11.10.2026).
4. Dewaele J.-M. The emotional force of swearwords and taboo words in the speech of multilinguals // *Journal of Multilingual and Multicultural Development*. 2004. Vol. 25, No. 2-3. P. 204-222. DOI: 10.1080/01434630408666529.
5. Rudra K., Rijhwani S., Begum R., Bali K., Choudhury M., Ganguly N. Understanding language preference for expression of opinion and sentiment: what do Hindi-English speakers do on Twitter? // *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*. Austin: Association for Computational Linguistics, 2016. P. 1131-1141. DOI: 10.18653/v1/D16-1121.

6. Acuña Ferreira A.V. Code-switching and emotions display in Spanish/Galician bilingual conversation // *Text & Talk*. 2017. Vol. 37, No. 1. P. 47-69. DOI: 10.1515/text-2016-0036.
7. Karimpour S., De Costa P., Nazari M. Emotions in switching the code: contributions for English language teachers' identity construction // *Journal of Multilingual and Multicultural Development*. 2026. Vol. 47, No. 3. P. 1528-1540 (published online 2024). DOI: 10.1080/01434632.2024.2429413.
8. Gazez A.A. Emotional expression in two languages: bilingual perspectives on language choice and emotional authenticity // *Central Asian Scientific Journal*. 2026. No. 1(29), Vol. 2. P. 213-217.
9. Lee S.Y.M., Wang Z. Emotion in code-switching texts: corpus construction and analysis // *Proceedings of the Eighth SIGHAN Workshop on Chinese Language Processing*. Beijing: Association for Computational Linguistics, 2015. P. 91-99. DOI: 10.18653/v1/W15-3116.
10. Tang T., Tang X., Yuan T. Fine-tuning BERT for multi-label sentiment analysis in unbalanced code-switching text // *IEEE Access*. 2020. Vol. 8. P. 193248-193256. DOI: 10.1109/ACCESS.2020.3030468.
11. Vilares D., Alonso M.A., Gómez-Rodríguez C. EN-ES-CS: an English-Spanish code-switching Twitter corpus for multilingual sentiment analysis // *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)*. Portorož: ELRA, 2016. P. 4149-4153. URL: <https://aclanthology.org/L16-1655/> (accessed: 11.10.2026).
12. Hu N., Zhang J., Pavlou P.A. Overcoming the J-shaped distribution of product reviews // *Communications of the ACM*. 2009. Vol. 52, No. 10. P. 144-147. DOI: 10.1145/1562764.1562800.
13. Савирдинова А. Сленг в современном языке молодёжи: влияние социальных сетей // *Central Asian Scientific Journal*. 2026. № 2(30), Т. 1. С. 569-572.
14. Anuarova S.A., Konarova A.B. Language, psyche, and society: cognitive and social interrelations in a multilingual context // *Central Asian Scientific Journal*. 2026. No. 2(30), Vol. 1. P. 140-151.
15. Assan R. KazSwitch: a controlled benchmark for Kazakh-Russian code-switching in multilingual language models // *Central Asian Scientific Journal*. 2026. No. 2(30), Vol. 3. P. 65-72.
16. Institute of Smart Systems and Artificial Intelligence (ISSAI). KazSAnDRA: Kazakh Sentiment Analysis Dataset of Reviews and Attitudes. GitHub repository. URL: <https://github.com/IS2AI/KazSAnDRA> (accessed: 11.10.2026).
17. Korobov M. Morphological analyzer and generator for Russian and Ukrainian languages // *Analysis of Images, Social Networks and Texts (AIST 2015)*. Communications in Computer and Information Science. Cham: Springer, 2015. P. 320-332. DOI: 10.1007/978-3-319-26123-2_31.
18. Wikimedia Foundation. Wikipedia (Kazakh), dump of 01.11.2023, dataset "wikimedia/wikipedia", configuration 20231101.kk. URL: <https://huggingface.co/datasets/wikimedia/wikipedia> (accessed: 11.10.2026).

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