Mapping Effective Teaching with Topic Modeling

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Abstract. Teacher effectiveness is of utmost importance with respect to educational quality, and determines levels of student accomplishment and societal outcomes in general. Through the Latent Dirichlet Allocation (LDA) topic modeling of Russian language lessons, this study investigates how well the observed teaching practices align with Federal State Educational Standards (FSES, FGOS in Russian) and contrasts the findings for more and less effective teachers. More effective teachers design their lessons around central topics within the curriculum, they have greater coherence and alignment with FSES goals. Less effective teachers pick generic topics the lessons hardly ever touch upon. The proposed procedure not only yields insights on teaching strategies but also provides a template for the development of data-driven tools for assessing instructional quality in various educational settings. The results confirm the ability of topic modeling to advance the appraisal of actual educational practices in Russia and beyond.

Keywords: Corpus Linguistics, Topic Modeling, Pedagogical Practices.

1 Introduction

Teacher effectiveness is a pillar of educational quality and directly affects student achievement, student engagement, and social and economic consequences for the wider community. For decades, research has focused on discerning which pedagogical practices correspond with high-quality instruction [7, 8, 21], but the difficulty of systematic evaluation arises from the subjectivity of teaching as well as its acute contextuality. Traditional methods of assessing an instructional event, for example, classroom observations [20], student surveys [6], or analyses of standardized test score distributions [9], have characteristics of being manpower-intensive and methodologically weak because they take a snapshot of an isolated event that is highly prone to rater bias and scalability issues. Within the Russian context, where a centralized curricular framework collides with a highly diverse educational landscape on the regional level, there is now an increasing urgency for developing data-driven instruments for assessing instructional quality.

Advances in computational linguistics provide an enterprising avenue in this regard. Unsupervised machine learning methods enable researchers to extract latent patterns from mostly unstructured data in textual format, such as lesson transcripts, which can be used as evidence for inference about classroom interaction and pedagogical strategies. In particular, topic modeling (TM) algorithms have shown promise in extracting thematic structures from different corpora such as social networks corpora [10, 14], fiction corpora [4, 5], etc.

Topic modeling remains to be scarcely explored in non-English-speaking educational contexts, where linguistic, cultural, and institutional factors might have different impacts on the design of teaching practices. This study bridges this gap by employing topic modeling to examine lesson transcripts from Russian secondary schools, aiming to identify language markers distinguishing more and less effective educators.

2 Related Works

In the educational research field, topic modeling procedures have demonstrated a very similar methodology when applied to different teaching challenges, including teacher self-evaluation and environmental impact on student learning. The common thing here is the application of Latent Dirichlet Allocation (LDA), although its adaptations differ across linguistic and institutional settings.

Most studies stress the need for a rigorous preprocessing pipeline consisting of tokenization, stop-word removal, and lemmatization to deal with noise, especially for morphologically rich languages like Spanish [3] or Chinese [31]. The importance of human validation has been recognized in each of the frameworks, whether for the purpose of refining algorithmically generated topics [24] or to make sense of the polarity of sentiment in climate-impacted classrooms [12]. Pioneering hybrids like in [31], which pursue the integration of term-frequency matrices (QTFM) with hierarchical Dirichlet processes (HDP), indicate the recognition of a tension between scalability and semantic precision. Much like text network modeling [3] and sentiment analysis [12], topic modeling shows the compatibility with other techniques so as to enrich insights.

Competency-based education (CBE) has seen a global surge in attention, driven by the need for 21st-century skills and the evolving demands of modern society. The research [16] highlighted that international organizations like the OECD have played a pivotal role in steering educational discourses toward sustainability and inclusivity. The findings emphasized themes such as "learning skills" and "teacher training," signaling a fundamental shift from traditional knowledge-based models to frameworks that prioritize competencies. This growing interest reflects a broader understanding that education must prepare individuals not merely for rote knowledge retention but for adaptable, real-world application.

In parallel, the flipped classroom model has emerged as a transformative pedagogical approach. Ozyurt [15] conducted a comprehensive analysis that revealed sixteen key themes, with topics like "Performance and perception," "Nursing education," and "Effectiveness and motivation" standing out. This approach, characterized by its emphasis on student-centered learning environments, has proven highly adaptable during the pandemic. By shifting traditional in-class instruction to pre-class activities and using classroom time for engagement and reinforcement, the flipped model has offered a dynamic and effective solution for many educational contexts.

The COVID-19 pandemic itself became a watershed moment for educational research. Vijayan [26] studied topical landscape studies and distilled six major themes, the effects on higher education institutions, the implementation of digital tools, and the mental health conditions of students. The pandemic exposed and deepened the pre-existing inequalities in education; technological inequality arose as one issue of concern, especially in lower-income areas and some parts of the developed world. As much as these challenges surfaced, the pandemic also offered opportunities for educators and institutions to think creatively about ways of being and implement digital models that may have a lasting impact to beyond the pandemic.

A notable trend in physics education research, as explored in [29], highlights the dual identity of physics education as both a scientific and pedagogical field. By applying topic modeling to extensive journal archives, this study identified shifts in research focus over decades. Topics such as pedagogical content knowledge (PCK), assessment methodologies, and gender-related educational outcomes have gained prominence, while traditional themes like introductory physics and problem-solving have seen relative declines. The reliance on LDA facilitated a broad yet nuanced categorization of research themes, enabling insights into evolving pedagogical priorities and underexplored areas.

In a broader educational context, Weng et al. [28] employed topic modeling to examine peer interaction in online and mobile learning environments within higher education. Their study spanned nearly three decades and utilized sophisticated clustering methods to synthesize diverse research themes. The findings underscored the growing role of digital peer assessment, engagement innovations, and collaborative learning technologies. Notably, the study revealed an increasing emphasis on asynchronous peer feedback mechanisms, anonymity in assessments, and the integration of artificial intelligence in learning management systems. The topic modeling approach not only categorized research trends but also highlighted the interplay between technological advancements and pedagogical strategies.

The integration of topic modeling in education research offers a powerful means of systematically analyzing vast educational datasets. However, current studies face challenges in balancing scalability with semantic precision, addressing linguistic complexities, and ensuring meaningful human validation. To move forward, we propose using topic modeling approaches for detecting more and less effective teaching practices by describing common topics that were mentioned within specific classes and comparing them with existing secondary school curricula.

3 Experimental Design

The corpus described in [11] is used for this study. At first, a dataset of more than 50 video-recorded secondary school lessons was provided by SberObrazovanie LLC (see the Acknowledgments Section), the textual data was obtained for further analysis. Nevertheless, it is important to note that the compiled corpus is not limited to textual data alone. The research team led by E.I. Riekhakainen is developing a multi-level annotation of the corpus of teaching practices, including, in particular, the annotation of pauses [27]. Building on this dataset, SberObrazovanie LLC identifies more effective teachers as a group of people that share certain features: linguistic markers and patterns, metaphors and means to regulate the mental condition of students. In this paper, the leading linguistic feature under study is word representations of LDA topic models.

Subject subcorpora of more and less effective teachers are selected, with each subject subcorpus containing at least two transcribed lessons. Thus, for topics modeling, a dataset with a total volume of about 77,000 words was compiled for topic modeling. The Russian Language (5th, 6th and 7th grades) and Literature (5th grade) are taken as subjects for the experiment as the most representative ones in different levels of secondary education. The second reason for choosing these subjects lies in the homogeneity of lessons of The Russian Language and Literature in Russian schools. The subjects share the same role in fostering national identity and cultural understanding. In future research, it is necessary to develop a topic modeling methodology for lessons of different domains, e.g., biology, mathematics and literature.

The developed Python script is designed to perform topic modeling on the pedagogical dataset using Latent Dirichlet Allocation (LDA). It continues to find traction because it derives meaningful topics from large documents with the least amount of supervision, thus making it useful for exploratory analysis in many fields, ranging from text mining to social sciences [1, 2]. Interpretability, simplicity, and scalability are the reasons for the sustained popularity of LDA in research and applications [23].

To prepare the data for analysis, several preprocessing steps are applied: tokenization, lemmatization using the Stanza library [17], and removal of stopwords. After this, the cleaned and lemmatized text is converted into a bag-of-words format through the creation of a Gensim dictionary [18]. Next, the script performs topic modeling by applying the LDA algorithm to the processed text corpus. It experiments with different numbers of topics, ranging from 3 to 15, to evaluate the optimal configuration. During this process, the model's perplexity and coherence scores are computed for each topic count. Perplexity serves as a measure of how well the model generalizes to unseen data, with lower values signifying better generalization [25]. The coherence score assesses the semantic consistency of topics, with higher values indicating more meaningful and interpretable topics [13]. These evaluation metrics are visualized using Matplotlib, providing a clear indication of the optimal number of topics. Some results are presented in Figures 1 and 2. Figure 1 shows suggests moderate topic structure in the lessons of less effective teachers, though with signs of topical redundancy. The lack of sharp coherence peaks may indicate topical overlap. Figure 2 demonstrates a clearer peak in coherence and lower perplexity values around 5 topics, it may indicate more stable topics from semantic point of view.

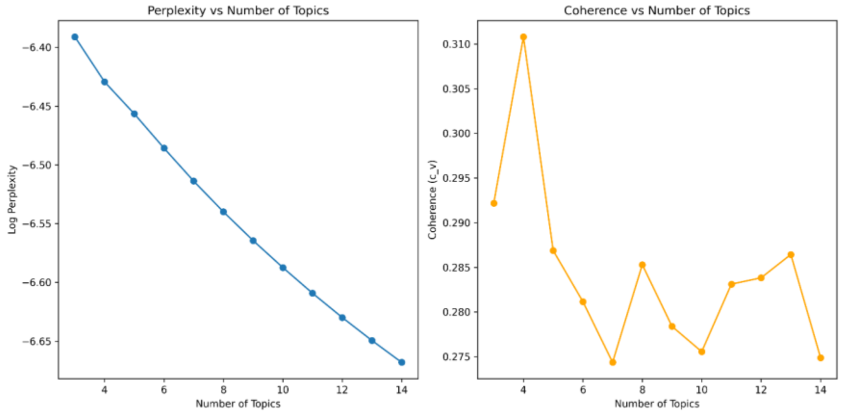

Fig. 1. The perplexity and coherence scores for less effective teachers of the Russian Language (the 7th Grade).

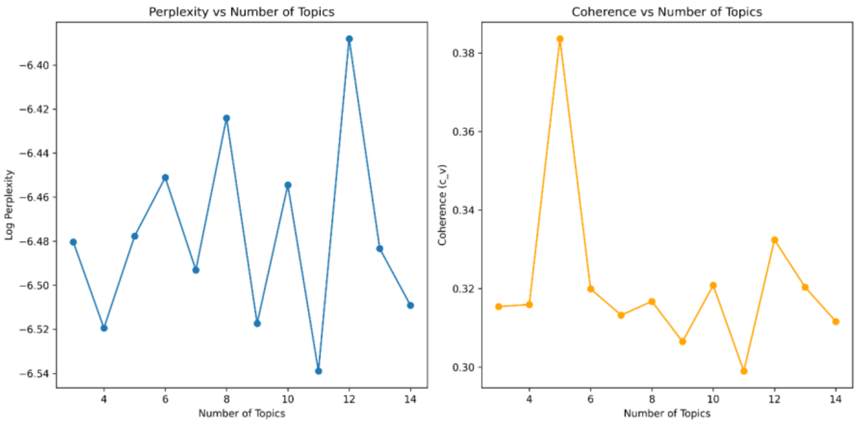

Fig. 2. The perplexity and coherence scores for more effective teachers of the Russian Language (the 5th Grade).

Once the best model is selected based on the highest coherence score, the script outputs the identified topics, displaying their topical terms. The set of words are presented in Table 1. To improve readability, the table is split into subtables by grade, subject and effectiveness parameters, with resultant models highlighting key differences between more and less effective teaching patterns.

Table 1. The resultant sets of topic models for more and less effective teachers.

Grade	Subject	Effectiveness	Topic Number	LDA Topics
5	Literature	More Effective	0	byt' (to be), voyna (war), rebyata (children), mal'chik (boy), stikhotvoreniye (poem), moch' (can), god (year), mal'chishka (little boy), verny (correct)
			1	byt' (to be), Vasyutkiy (Vasyutka), rebyata (children), verny (correct), les (forest), davat' (to give), pravil'no (correctly), ozero (lake), pervy (first)
			2	byt' (to be), otets (father), Vasya (Vasya), khoroshiy (good), moch' (can), vnimanie (attention), schitat' (to consider), chelovek (person), khotet' (to want)
5	Literature	Less Effective	0	byt' (to be), rebyata (children), Nikita (Nikita), khoroshiy (good), moch' (can), rasskaz (story), govorit' (to speak), molodets (well done),
			1	rebyata (children), byt' (to be), god (year), Robinzon (Robinson), Kruzo (Crusoe), ostrov (island), chetyre (four), Defo (Defoe), zhizn' (life)
			2	byt' (to be), rebyata (children), Nikita (Nikita), god (year), Robinzon (Robinson), ostrov (island), Kruzo (Crusoe), moch' (can)
5	Russian	More Effective	0	prilagatel'noye (adjective), byt' (to be), rod (gender), pisat' (to write), okonchaniye (ending), chislo (number), khoroshiy (good), slovo (word), vopros (question)
			1	glagol (verb), byt' (to be), vremya (tense), govorit' (to speak), delat' (to do), proyti (now we know), suffiks (suffix), okonchaniye (ending), forma (form)
			2	prilagatel'noye (adjective), kratkiy (short), khoroshiy (good), pisat' (to write), myagkiy (soft), znak (sign), shipyashchiy (hissing), byt' (to be), vopros (question)
			3	slovo (word), byt' (to be), predlozheniye (sentence), koren' (root), khoroshiy (good), rech' (speech), moch' (can), delat' (to do), zvuk (sound)
			4	rod (gender), prilagatel'noye (adjective), okonchaniye (ending), chislo (number), byt' (to be), pisat' (to write), padezh (case), sushchestvitel'ny (noun), sushchestvitel'noye (noun)
6	Russian	More Effective	0	chislitel'ny (numeral), prostoy (simple), byt' (to be), sostavnoy (compound), slovo (word), zapisyvat' (to write down), dva (two), poryadkovy (ordinal), kolichestvenny (quantitative)
			1	byt' (to be), chislitel'ny (numeral), davat' (to give), zapisyvat' (to write down), god (year), padezh (case), sorok (forty), pyat' (five), okonchaniye (ending)

Grade	Subject	Effectiveness	Topic Number	LDA Topics
			2	tsely (whole), chislitel'ny (numeral), devyat' (nine), davat' (to give), pribavit' (to add), tri (three), devyanosto (ninety), drobny (fractional), chetyre (four)
			3	pisat' (to write), suffiks (suffix), slovo (word), byt' (to be), khoroshiy (good), okonchaniye (ending), defis (hyphen), slity (merged), narechiy (adverb)
7	Russian	More Effective	0	byt' (to be), predlozheniye (sentence), soyuz (conjunction), chast' (part), prilagatel'noye (adjective), tekst (text), podchinitel'ny (subordinating), vopros (question), khoroshiy (good)
			1	byt' (to be), prilagatel'noye (adjective), tekst (text), stil' (style), tema (theme), olen' (deer), dvadtsat' (twenty), pisat' (to write), moch' (can)
			2	soyuz (conjunction), chast' (part), byt' (to be), predlozheniye (sentence), podchinitel'ny (subordinating), vopros (question), khoroshiy (good), rebyata (children), davat' (to give)
5	Russian	Less Effective	0	prilagatel'noye (adjective), byt' (to be), padezh (case), vopros (question), rebyata (children), slovo (word), imya (name), predlozheniye (sentence), delo (matter)
			1	byt' (to be), padezh (case), vopros (question), prilagatel'noye (adjective), rebyata (children), slovo (word), okonchaniye (ending), predlozheniye (sentence), delo (matter)
			2	byt' (to be), slovo (word), vopros (question), padezh (case), rebyata (children), prilagatel'noye (adjective), delo (matter), predlozheniye (sentence), imya (name)
			3	byt' (to be), vopros (question), padezh (case), delo (matter), slovo (word), okonchaniye (ending), rebyata (children), verny (correct), molodets (well done), zapisat' (to write down)
			4	byt' (to be), padezh (case), vopros (question), rebyata (children), slovo (word), okonchaniye (ending), predlozheniye (sentence), delo (matter), davat' (to give)
			5	prilagatel'noye (adjective), byt' (to be), kratkiy (short), rod (gender), predlozheniye (sentence), chestny (honest), bely (white), prekrasny (beautiful), okonchaniye (ending)
			6	prilagatel'noye (adjective), kratkiy (short), predlozheniye (sentence), byt' (to be), rod (gender), bely (white), chislo (number), yasny (clear), prekrasny (beautiful)

Grade	Subject	Effectiveness	Topic Number	LDA Topics
			7	prilagatel'noye (adjective), rebyata (children), imya (name), rod (gender), pravil'no (correctly), chislo (number), zapyataya (comma), byt' (to be), predlozheniye (sentence)
6	Russian	Less Effective	0	[Low-weight topic: byt' (to be), slovo (word), predlozheniye (sentence), narechiy (adverb), mestoimeniye (pronoun), moch' (can), delat' (to do), pisat' (to write), sleduyushchiy (next)
			1	byt' (to be), slovo (word), sposob (method), narechiy (adverb), moch' (can), suffiks (suffix), sufliksal'ny (suffixal), pristavochny (prefixal)
			2	byt' (to be), narechiy (adverb), khoroshiy (good), predlozheniye (sentence), priznak (feature), dva (two), nayti (to find), slovo (word), chast' (part)
			3	os'minozhkiy (octopus-like), predlozheniye (sentence), bank (bank), byt' (to be), variant (variant), delat' (to do), proveryat' (to check), mestoimeniye (pronoun), stavit' (to put)
			4	byt' (to be), predlozheniye (sentence), narechiy (adverb), nayti (to find), mestoimeniye (pronoun), slovo (word), khoroshiy (good), rod (gender), chislo (number)
			5	predlozheniye (sentence), mestoimeniye (pronoun), voprositel'ny (interrogative), otnositel'ny (relative), slozhny (complex), byt' (to be), khoroshiy (good), pravil'no (correctly), vtoroy (second)
7	Russian	Less Effective	0	byt' (to be), zapyataya (comma), slitny (together), nuzhny (needed), predlozheniye (sentence), pisat' (to write), dva (two), slovo (word), razdel'no (separated), stavit' (to put)
			1	predlozheniye (sentence), byt' (to be), slitny (merged), zapyataya (comma), pisat' (to write), deeprichastny (adverbial participle), moch' (can), nuzhny (needed), oborot (construction)
			2	byt' (to be), predlozheniye (sentence), oshibka (mistake), moch' (can), deeprichastny (adverbial participle), smotret' (to look), oborot (construction), nepravil'ny (incorrect), pravil'no (correctly)
			3	byt' (to be), predlozheniye (sentence), oshibka (mistake), zapyataya (comma), nuzhny (needed), moch' (can), pravil'no (correctly), oborot (construction), pisat' (to write)

Additionally, an interactive visualization is generated using pyLDAvis [22]. It allows for a deeper exploration of topic distributions; an example is presented in Figure 3. The relatively even spacing and non-overlapping nature of the circles show a set of distinct topics in the discourse of more effective teachers. Another important finding in Figure 3 is that the Stanza lemmatizer output has several erroneous forms such as "*padekhoy*" and “*pristavky”*. These artifacts stem from limitations in lemmatization accuracy for Russian as a morphologically rich language, especially when there are colloquial words in transcribed data.

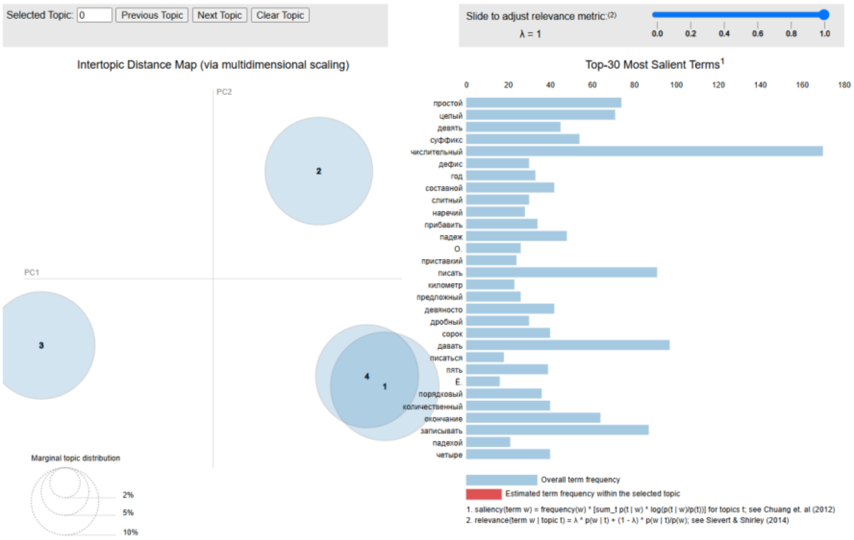

Fig. 3. The visualization of topic models for more effective teachers of the Russian Language (the 6th Grade).

4 Results and Discussion

4.1 The Russian Language, the 5th Grade

The comparative analysis of LDA topic modeling results for more effective (ME) and less effective (LE) Russian language teachers in Grade 5 reveals significant differences in curricular alignment with Federal State Educational Standards (FSES, FGOS in Russian), as outlined in [19] proposed by the Institute for Education Development Strategy of the Russian Academy of Education, a pivotal authority in shaping evidence-based Russian educational policies and conducting advanced research. Although Federal Working Programs (FWP, FRP in Russian) are generally assumed to play a role in operationalizing educational standards by providing recommended content sequencing and timelines, it is FSES that sets these standards and expected outcomes. It is the main reason for referring to FSES in the current paper.

The ME teachers’ topics demonstrate structured adherence to FSES thematic planning, particularly in core linguistic domains such as morphology, syntax, and orthography. For instance, high-coherence ME topics like Topic 1 (*“glagol”, “vremya”, “suffiks”* — *verb, tense, suffix*) and Topic 4 *(“rod”, “padezh”, “chislo”* — *gender, case, number*) explicitly reflect FSES objectives for noun declension, verb conjugation, and grammatical gender, mirroring the curriculum’s emphasis on systematic progression from phonetics to syntax. Conversely, the LE teacher’s topics exhibit fragmentation, with redundant themes such as Topics 0–2 and 4 (*"vopros", "padezh", "rebyata" — question, case, children*) lacking specificity and failing to address advanced FSES requirements like complex sentence structures or direct speech punctuation. This divergence may suggest that effective teachers prioritize FSES-mandated content sequencing, whereas less effective ones rely on generic or repetitive terminology.

A critical distinction lies in semantic coherence and pedagogical focus. The ME model's topics, such as Topic 2 (*"kratkiy", "myagkiy", "shipyashchiy" — short, soft, hushing*), align with FSES orthography units on spelling rules and phonetic analysis, while Topic 3 (*"slovo", "rech'", "zvuk" — word, speech, sound*) correlates with text composition and editing standards. These topics reflect a hierarchical structure, progressing from foundational concepts to applied skills. In contrast, the LE model's low-coherence themes, including Topic 3 (*"verny", "zapisat'", "molodets" — correct, write down, well done)*, reveal an overemphasis on procedural language and classroom management rather than linguistic content, deviating from FSES's content-driven goals.

Temporal relevance analysis, considering the modeling data was collected at the end of School Term 3 (the end of March in the Russian Federation), underscores the ME teachers' alignment with FSES pacing. By this stage, FSES expects advancement to applied grammar and text analysis, reflected in ME topics like Topic 1 (*"proyti", "form" — now we know, form*) on verb forms and Topic 3 on phonetic and textual linkages. In contrast, LE topics stagnate in basic vocabulary reinforcement (e.g., Topic 7: *"imya", "chislo", "predlozheniye" — name, number, sentence*), failing to address School Term 3 goals such as *"redaktirovaniye teksta" (text editing)* or *"intonatsionnye normy" (intonation norms)*. This misalignment suggests that less effective teachers lag in curricular progression and may leave students underprepared for Year 5 final assessments.

4.2 The Russian Language, the 6th Grade

From the FSES thematic planning document, the curriculum for the sixth-grade Russian language includes topics such as types of speech (narrative, description, reasoning), functional varieties of language (official, scientific), and deep engagement with linguistic structures like nouns, adjectives, numerals, pronouns, and verbs. Activities focus on developing skills in creating and analyzing various text forms, understanding lexical nuances, and applying grammatical norms.

In the LDA topics derived from the more effective teachers' lessons, there is a strong emphasis on numerals, word formation, and syntax. Topical words such as *"chislitel'ny" (numeral)*, *"prostoy" (simple)*, *"sostavnoy" (compound)*, *"slovo" (word)*, and *"suffiks" (suffix)* suggest a focus on understanding structural aspects of language, particularly in relation to numbers and word formation rules. This aligns well with the FSES emphasis on morphological analysis and syntactic functions, indicating that these teachers' lessons are closely following the curriculum goals.

In contrast, the LDA topics from the less effective teachers' lessons (LE) are characterized by more generic and less focused terms. While topical words like *"byt'" (to be)*, *"slovo" (word), "predlozheniye" (sentence)* touch on fundamental aspects of language, they do not reflect the detailed engagement with linguistic categories and structures expected by the FSES standards. This suggests that the lessons might not be as rigorously aligned with the curriculum's targeted learning outcomes.

4.3 The Russian Language, the 7th Grade

The comparative analysis of LDA topic modeling results for effective and less effective 7th grade Russian language teachers reveals nuanced differences in their alignment with the FSES thematic planning. The FSES curriculum emphasizes blocks such as morphology (participles, adverbs), functional language varieties (styles, text analysis), and syntax (conjunctions, sentence structure), alongside practical activities like text creation, error correction, and grammatical application. ME teachers' topics (0, 1, and 2) broadly align with these areas, focusing on conjunctions (*"soyuz", "podchinitel'ny" — conjunction, subordinating*), text analysis (*"tekst", "stil'" — text, style*), and parts of speech (*"prilagatel'noye" — adjective*). However, the lack of specificity in these topics, such as limited emphasis on morphological details (e.g., participles) or stylistic nuances, raises questions about depth.

At the same time, less effective teachers' topics (0, 1, 2, and 3) highlight practical challenges: frequent references to punctuation (*"zapyataya" — comma*), spelling (*"slitny", "razdel'no" — together, separated*), and error analysis (*"oshibka", "nepravil'ny" — mistake, incorrect*), particularly in deeprichastie (*"deeprichastny" — an adverbial formed from a Russian verbal part of speech called 'deeprichastie'*) and sentence construction. These topics reflect a reactive focus on correcting common mistakes, aligning with FSES emphasis on applied skills but suggesting fragmented coverage of the curriculum's broader thematic goals. The presence of error-centric terms in LE topics may indicate prioritization of remedial instruction over holistic thematic mastery, potentially linked to addressing student difficulties observed by the third quarter's end. While both groups touch on FSES elements, ME's alignment with structural components (e.g., conjunctions, text types) versus LE's emphasis on error correction suggests effectiveness correlates not with mere coverage of curriculum topics but with how comprehensively and proactively these topics are integrated into pedagogical practice. ME's approach appears more congruent with FSES integrative goals, whereas less effective teachers focus on troubleshooting specific issues, though relevant, may reflect a less systematic implementation of the planned curriculum.

4.4 Literature, the 5th Grade

In the subcorpus of more effective teachers, the frequent occurrence of terms like *"voyna" (war), "mal'chik" (boy)*, and *"stikhotvoreniye" (poem)* suggests a focus on core literary themes and texts from the curriculum, such as patriotism and childhood narratives. This alignment implies that they offer lessons reflecting structured literary analysis and foster a deeper understanding of literature. Conversely, less effective teachers often mention *"Robinzon" (Robinson)* and *"ostrov" (island)*, indicating an overemphasis on Daniel Defoe's "Robinson Crusoe", a text not directly prescribed by the curriculum, which may lead to deviations from the thematic objectives set by FSES. However, this interpretation (and many of them) should be approached with caution.

The presence of topical words such as *Robinzon" (Robinson)* and *"ostrov" (island)* in LDA output does not unambiguously indicate disproportionate instructional focus. It may result from isolated lessons or even model noise.

Furthermore, their reliance on conversational terms such as *"molodets"* (*well done*) and *"govorit'"* (*to speak*) suggests a classroom approach more focused on interaction than literary analysis. Although these results suggest that teacher effectiveness correlates with curriculum adherence, the variety of fiction works in literature may inherently bias the thematic analysis. It is not true for teachers of the Russian Language since students are often offered a limited set of rules to learn. Nevertheless, the resultant models indicate that more effective teachers present a more cohesive and planned thematic approach, closely reflecting curriculum objectives.

5 Conclusion and Future Work

The present study underscores the potential of topic modeling as a methodological tool for examining the relationship between teacher effectiveness and adherence to curriculum planning within lessons. The analyses reveal notable distinctions between the instructional approaches of more and less effective teachers and suggest that pedagogical effectiveness may be linked to the structured integration of curricular topics. To build on these findings, future research should investigate the influence of teacher training programs and the availability of educational resources on lesson coherence and topical alignment. Moreover, expanding the scope of analysis to include other educational levels and subject areas could offer a broader perspective on the relationship between curriculum adherence and teaching effectiveness.

Although basic LDA procedures are used in the paper, it is worth mentioning that future work could explore more advanced topic modeling approaches, such as neural topic models (NTMs) or models with contextual embeddings. According to [30, p. 4720], "…although the marriage between NTMs and language models is still an emerging area, we expect to see more developments in this important direction." In this regard, there is a chance to enhance the current results, as well as depth of pedagogical analysis.

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