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Ontology-Based Digital Learning Platform for Kazakh Language in Primary School: Curriculum-Aligned Semantic and Adaptive Approach

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ABSTRACT

This study presents the design, implementation, and evaluation of an ontology-based digital learning platform for teaching Kazakh language in primary school. The platform is developed using ontology modeling tools, including OWL, RDF, and Protégé, and integrates adaptive learning mechanisms to enhance student engagement and learning outcomes. A quasi-experimental pre-test/post-test design without a control group was employed, involving 200 students across grades 2–4 in Astana. The platform organizes educational content semantically, covering six language competencies: vocabulary, grammar, spelling, reading, writing, and text comprehension. Statistical analysis revealed significant improvements between pre- and post-tests ($p < 0.001$), with average performance gains of 16–21% and Cohen's d effect sizes up to 1.14, indicating moderate to large educational impact. The study demonstrates that ontology-based structuring facilitates automated content generation, semantic feedback, and personalized learning paths. Moreover, the platform supports interpretable reasoning for educators, enabling targeted interventions and monitoring. The results provide preliminary evidence that integrating curriculum-aligned ontologies into intelligent learning systems enhances language skill acquisition, independent learning, and classroom engagement. This research contributes a scalable framework for developing educational technologies tailored to agglutinative languages, offering both practical guidance and a foundation for future AI-supported learning tools in primary education.

1. INTRODUCTION

In today's society, young schoolchildren are increasingly immersed in digital entertainment, reducing the amount of meaningful verbal interaction. Children aged 5 to 8 spend an average of more than two hours a day using mobile devices, primarily passively consuming media content [1]. This practice often replaces face-to-face communication and limits opportunities for natural speech development. As a result, educators note increasing difficulties in elementary school students with articulation, grammatical accuracy, and speech comprehension [2, 3]. UNESCO also warns that excessive use of screen devices without pedagogical support negatively impacts the development of oral language and critical thinking in children [4, 5]. These issues are particularly noticeable in the teaching of the Kazakh language, where modern and high-quality digital learning materials are still insufficient. At the same time, the use of artificial intelligence within language education has been growing steadily. In Kazakhstan, this development is reflected in recent achievements in Kazakh speech recognition [6] and in the creation of ontologically structured linguistic resources [7].

International research also confirms the effectiveness of intelligent tutoring systems (ITS) in primary schools [8]. However, for agglutinative languages such as Kazakh, existing solutions are often fragmented, not aligned with the curriculum, and do not reflect complex morphological relationships [9-11]. Consequently, the opportunities that AI technologies could offer to education do not fully align with the practical conditions faced by teachers and students in Kazakhstan [12, 13].

One promising approach to solving this problem is the development of educational resources based on ontologies. Recent research has shown that intelligent tutoring systems supported by artificial intelligence can enhance learning processes and provide adaptive support for students [14]. For Kazakhstan, such tools hold significant value not only in terms of pedagogy, but also for supporting the broader development and visibility of the Kazakh language in the digital environment [15].

In this context, the present study focuses on developing an ontological model that corresponds to the Kazakh language curriculum for primary school and is grounded in the official textbooks for grades 2–4. The paper addresses the following research questions:

RQ1. What linguistic elements should be represented in the educational ontology of the Kazakh language?

RQ2. What types of semantic relationships are most effective for ontological modeling of linguistic concepts?

RQ3. How can the created ontology be integrated into intelligent learning platforms?

Key findings of the study include:

- one of the first ontology-based models for Kazakh language learning aligned with the curriculum for grades 2–4;
- integration of ontology into an intelligent learning system with semantic feedback;
- an experimental test of effectiveness on a sample of 200 primary school students (approximately equal numbers of girls and boys), which showed a statistically significant improvement in language skills;
- creation of a scalable foundation for digital education based on an ontological approach adapted to agglutinative languages.

Thus, the presented study contributes to the development of ontology-based digital learning tools that support structured language learning and feedback for primary school students.

2. LITERATURE REVIEW

Advances in digital technologies, the emergence of semantic methods, and the introduction of innovative pedagogical practices have considerably reshaped approaches to language instruction. However, the level of their integration and actual effectiveness depends on the specific features of a particular language, the educational environment, and the architecture of the systems themselves. This section examines the main areas of research related to the application of ontologies and semantic models in education, personalized learning, and adaptive technologies.

Many researchers note that the ontological approach helps organize educational material and formalize subject knowledge. Thus, Ahmed and Kovacs [16, 17] showed that the use of ontologies in learning management systems (LMS) contributes to better organization of content and automatic establishment of links between concepts. Wongthongtham et al. [18] applied ontology to personalize learning by offering students materials based on semantic recommendations. However, these approaches are mainly focused on structuring content and do not take into account the features of linguistic relationships and grammatical dependencies.

A study by Tlepbergen and colleagues [19] examined the use of digital technologies in language policy in Kazakhstan, but did not develop ontological learning models. Overall, the existing body of work does not fully correspond to the primary school curriculum and has not yet been explicitly directed toward enhancing the language abilities of young learners studying Kazakh.

Work on semantic modeling demonstrates the potential for creating more meaningful and coherent learning materials. Bhardwaj et al. [20] proposed a model of semantic data interoperability, while Bratland and El Gami [21] and Kim et al. [22] explored ways to structure learning texts to enhance conceptual understanding. These studies have shown that semantic organization of knowledge helps students better understand material and be more engaged in the learning process. However, most such models are not specifically designed for language teaching and do not take into account the characteristics of agglutinative languages, where morphology and semantics are closely linked. Therefore, their use for developing Kazakh language skills remains limited.

In recent years, systems that allow for the adaptation of the learning process to each student have been actively developed. Jiang [23] and Murtaza et al. [24] proposed personalized e-learning models, and Ehsan and Li [25, 26] developed methods for predicting academic performance and creating individual learning paths. Such solutions do improve learning effectiveness, but in many cases, they rely on so-called "black boxes"-algorithms whose operation remains opaque to users. This makes it difficult to explain to students why the system suggests a particular answer or correction, especially when learning grammar. For elementary schools, where clear and explainable learning is essential, such models prove insufficiently pedagogical.

Research in the field of optimization approaches and digital educational ecosystems [27-31] shows significant progress in integrating data analysis methods and creating scalable learning platforms. Such systems cope well with processing large volumes of information and adapting to various conditions. However, they generally do not address issues of grammar teaching and semantic analysis, and are not targeted at younger students. Therefore, their use in teaching Kazakh remains limited.

Table 1 summarizes key related studies, highlighting their main contributions and limitations, and clarifying the research gap addressed in this work.

Table 1. Comparative analysis of ontology-based and AI-supported educational approaches

Study	Approach	Strength	Limitation	Gap Addressed in This Study
[16, 17]	Ontology-based LMS	Content structuring, concept linking	Not language-specific, no curriculum alignment	Adds curriculum-aligned ontology for Kazakh
[18]	Ontology and personalization	Adaptive recommendations	Focus on recommendation, not grammar learning	Adds semantic grammar feedback
[12]	Ontology from text	Automated ontology construction	No classroom validation	Adds real school experiment
[24]	AI-based learning systems	Personalization, prediction	“Black-box” models, low interpretability	Uses interpretable ontology reasoning
[7, 11]	Kazakh ontology resources	Linguistic data modeling	Not aligned with school curriculum	Aligns ontology with grades 2–4 curriculum
[19]	Digital language policy	Contextual insights	No ontology-based learning model	Provides practical ontology-based system

A review of the literature shows that significant progress has been made in ontology-based and AI-supported educational systems, including semantic structuring of learning content and adaptive learning mechanisms. These approaches have demonstrated the potential of ontologies for organizing knowledge and supporting personalized learning processes.

However, several limitations remain. Existing systems are typically not aligned with specific school curricula, provide limited support for language-specific grammatical structures, and rarely address the complexities of agglutinative languages. In particular, most approaches do not integrate semantic and morphological analysis in a way that is suitable for primary language education.

In the context of Kazakh language learning, these limitations are especially significant. Existing studies on Kazakh language resources and ontology-based approaches remain limited and are not fully adapted to the requirements of the primary school curriculum [7, 32-37].

This study addresses this gap by developing a curriculum-aligned ontology-based system tailored to the linguistic characteristics of Kazakh and validated in a real classroom setting.

3. METHODOLOGY

3.1 Experimental design

The experimental portion of the study utilized a pre-test/post-test design and was conducted at a comprehensive school in Astana, Kazakhstan. The total sample consisted of 200 primary school students, distributed across three grade levels.

The study involved:

- second-grade students – the school has 15 second-grade classes with a student population of 25 to 26 students; of these, 65 students (34 girls and 31 boys) were selected to participate in the experiment;
- 3rd grade students – a total of 13 parallels with a number of 25–26 students; the study included 68 students (33 girls and 35 boys);
- 4th grade students – represented by 12 parallels of 25–26 people; the sample included 67 students (32 girls and 35 boys).

Thus, the total sample consisted of 200 schoolchildren (99 girls and 101 boys), which ensured gender balance and representativeness of the data for analysis.

All participants completed standardized assessment tasks designed to evaluate six key language competencies: vocabulary, grammar, spelling, reading, writing, and text comprehension. All assessment tools were developed in accordance with the requirements of the Kazakh language state curriculum.

The experiment took place in two stages:

(1) preliminary stage - before the implementation of the ontological training platform (pre-test);

(2) control and results stage - after completion of the cycle of classes using the developed ontological system (post-test).

The experiment lasted twelve weeks, covering one full academic cycle and ensuring consistent progress in language skill development. The length of the intervention helped ensure the robustness of the findings and made it possible to evaluate the influence of the ontological learning model on students' learning quality with greater confidence.

This study employed a quasi-experimental pre-test/post-test design without a control group; therefore, the findings suggest a positive association between the use of the ontological learning system and improvements in language performance, rather than a definitive causal relationship.

3.2 Statistical analysis

To assess the effectiveness of the ontological learning model in a quantitative manner, statistical testing was carried out using the student's t-test for dependent samples (paired-samples t-test). This approach made it possible to detect consistent differences between the pre-test and post-test outcomes across all six evaluated competencies: vocabulary, grammar, spelling, reading, writing, and text comprehension.

Statistical significance of differences was determined at $p < 0.05$, which corresponds to generally accepted standards of empirical pedagogical research. For all obtained mean differences, 95% confidence intervals (CI) were additionally calculated, providing an assessment of the stability of the results and the reliability of the conclusions.

To evaluate the influence of the proposed model, Cohen's d was calculated as an effect size measure, enabling an assessment of the practical significance of the observed improvements. Values of $d = 0.6–0.8$ were interpreted as a moderate effect, and $d \geq 1.0$ as a high-intensity effect. The combined use of the p, CI, and d parameters provided a comprehensive assessment of the impact of the implemented ontology platform in terms of both statistical significance and the pedagogical significance of the identified improvements.

3.3 Methodological basis for the development of an ontological model based on linguistic and pedagogical analysis of Kazakh language textbooks (grades 2–4)

The methodological concept for developing the ontological model was based on the principles of systemic and content-oriented analysis of Kazakh language educational materials for elementary grades. Kazakh language textbooks for grades 2–4, hosted on the Okulyk.kz platform, served as the primary empirical base. These sources provided a representative corpus of texts reflecting the current state of linguistic and methodological approaches to teaching the Kazakh language in primary school. The development of the ontological model also builds on the authors' and related prior research on the formalization of Kazakh morphology, ontology-based linguistic resources, and the integration of natural language processing and large language models into educational and information systems [32-37].

The construction of the ontological model was carried out in accordance with a multi-level methodological scheme (see Figure 1), including interconnected stages of analysis, formalization and integration of data:

Identification of linguistic units is the primary selection of terms, word forms and grammatical constructions that occur in educational texts with high frequency.

Classification and selection – filtering the obtained data array according to three criteria: frequency of use, pedagogical significance and compliance with the requirements of the curriculum.

Semantic analysis is the determination of inter-level connections between lexical, morphological and syntactic elements that form the basis of the semantic structure of a language.

Ontological formalization is the representation of identified concepts and relationships as formal descriptors that enable machine processing and logical inference.

Integration into an ontological structure is the unification of the resulting semantic units into a unified knowledge system compatible with the architecture of intelligent learning platforms.

As a result of the analysis of textbooks, four key analytical dimensions were identified that determine the principles of selection and structuring of material:

- Frequency of use is the degree of representation of linguistic units in educational texts, which determines the priority of inclusion of elements in the ontology;
- Pedagogical relevance – the significance of units in terms of the development of students' speech, grammar and cognitive skills;
- Compliance with the curriculum – consistency of the allocated content with state educational standards and thematic lines of the course;
- Linguistic focus – incorporating grammatical, syntactic, and stylistic aspects that help ensure the model's overall pedagogical coherence.

Thus, the developed methodological structure ensured a systematic connection of linguistic and pedagogical analysis, allowing the formalization of the content of educational texts in the form of an ontological knowledge base.

Figure 1 presents the system architecture and the sequence of stages for constructing an ontology, including data extraction, semantic structuring, and integration into an intelligent learning environment. This architecture serves as the scientific and methodological foundation for the subsequent implementation of the model in digital educational technologies.

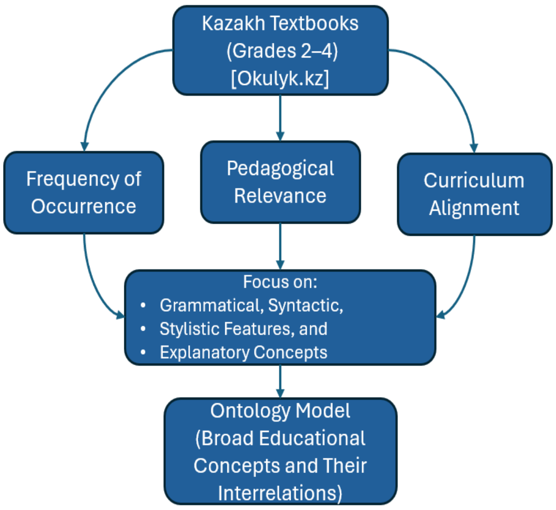


Figure 1. System architecture for ontology construction based on Kazakh language textbooks

Figure 2 presents the overall architecture of the developed intelligent learning assistant, built on the ontological model described in the previous section (see Figure 1). The system's architecture illustrates how users interact within the digital learning environment and shows how its functional components are interconnected.

Learners interact through a front-end interface - a chatbot or web application that provides a dialog-based form of communication with the system. The back-end implements knowledge processing and management modules: the Protégé ontology, a bank of learning tasks and exercises, and an analytics module that collects, analyzes, and visualizes learning data.

The functioning of all components is ensured by an orchestration layer that performs key functions of managing the learning process:

- processing and interpreting student responses;
- adapting the task sequence;
- dynamically generating feedback;
- interactive dialogue management.

The system architecture implements a three-level model that ensures logical integrity and adaptability of the educational process:

- User interaction level (Learner Interface) – includes a chatbot and a web application that provide interactive communication with students in real time.
- Orchestration Services – responsible for dialogue management, response evaluation, learning path adaptation, and personalized feedback generation.
- Knowledge and Content Layer – includes an ontology developed in the Protégé environment, a bank of educational tasks, as well as analytics modules that process educational data and support pedagogical decision-making.

This architecture ensures the structural consistency of all elements and supports adaptive and personalized learning, in which the learning path of each student is formed on the basis of their individual results, the dynamics of assimilation and semantic analysis of responses.

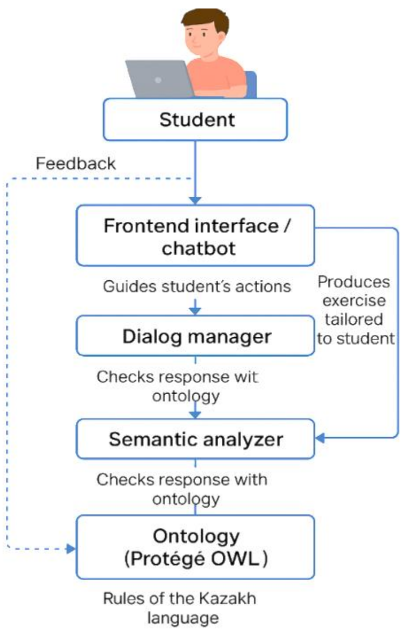


Figure 2. Architecture of the proposed AI-based teaching assistant

The system architecture is organized into several functional modules, including a user interface layer, a task management module, an ontology-based reasoning engine, a feedback generation module, and an analytics component. The ontology layer provides structured knowledge representation, while the rule-based reasoning module performs semantic analysis of student responses and supports feedback generation. The analytics module tracks student performance and supports adaptive decision-making. The AI-enhanced aspect of the system is reflected in adaptive feedback and dynamic task selection based on semantic analysis, rather than on machine learning models.

The system operates through a structured interaction workflow. First, the student accesses the platform via the user interface and receives a task selected from the task database based on the current topic and prior performance. The student's response is processed by the semantic analysis module, which uses the ontology to interpret the answer and identify errors. Based on this analysis, the system generates immediate feedback, including explanations and corrections.

The platform implements a feedback loop in which each student response informs subsequent task selection. Task sequencing is determined by performance indicators, enabling adaptive progression. The system supports two primary user roles: students, who complete tasks and receive feedback, and teachers, who monitor performance and guide the learning process. Performance data are stored in the analytics module and can be used to refine rule-based reasoning and improve system effectiveness over time.

3.4 Educational information system framework

From an information systems perspective, the proposed platform can be viewed as an educational information system that integrates multiple functional components and data flows. The system processes educational content starting from textbook materials, which are formalized into an ontology structure. This ontology serves as the basis for task generation, semantic analysis, and feedback mechanisms.

The data flow follows a structured pipeline: educational content is transformed into ontological representations, which are then used to generate learning tasks. Students interact with these tasks through the user interface, and their responses are processed by the semantic analysis module. The results are stored in the analytics module, which supports performance tracking and informs subsequent task selection. Teachers access this information to monitor student progress and adjust instructional strategies.

The system supports two primary user roles: students and teachers. Students engage with learning tasks and receive feedback, while teachers use the analytics module to evaluate performance and guide the learning process.

Functionally, the platform includes semantic querying based on ontology structures, grammar correction through rule-based reasoning, performance-based task recommendation, and learning analytics for tracking progress. These integrated components form a coherent educational information system that supports structured and data-driven language learning.

3.5 Ontology development and structuring

The developed Kazakh language ontology for primary education integrates more than 400 terms and concepts, systematically classified according to grammatical, lexical, syntactic, and functional properties. The structuring process resulted in the following components:

- 6 major categories of linguistic concepts;
- 27 subcategories aligned with specific topics of the national school curriculum;
- Over 120 lexical-grammatical units with explicitly defined semantic relations;
- Approximately 60 explanatory terms describing contextual and communicative language functions.

Figure 3 illustrates the schematic structure of the ontology, including the term selection process based on three key criteria-frequency of occurrence, pedagogical relevance, and curriculum alignment-and their integration into the final ontological model.

This structured approach ensures both semantic coherence and practical applicability, making the ontology relevant not only for classroom use by educators but also for developers of intelligent educational platforms. The choice of an ontology-based approach, rather than a generic knowledge graph, is motivated by its formal logical structure and interpretability, which ensure transparent reasoning and consistent knowledge representation within the educational domain.

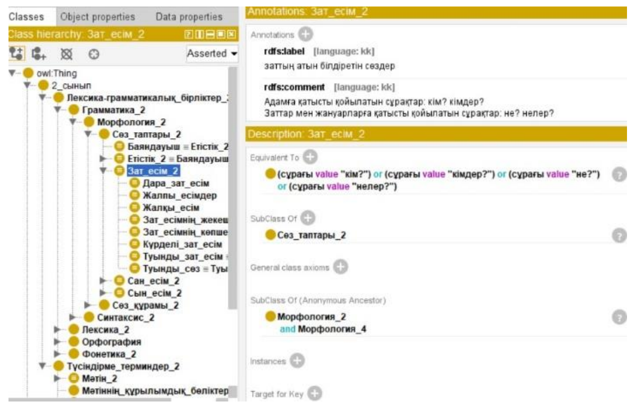


Figure 3. Lexical-grammatical units and explanatory terms in the ontology

Beyond nominal categories, the ontology provides a detailed representation of verbal concepts. For instance, the concept *Dara_etistik* (simple verb) is modeled as a subclass of Etistik_2 (Verb, Grade 2) and Morfologia_2 (Morphology, Grade 2). Semantic relations specify the typical question patterns used to identify verbs in Kazakh (e.g., “What does he/she do?”, “What did he/she do?”, “What happened?”). These verbal units are explicitly linked to syntactic roles such as the predicate (*baiandauysh*) and are integrated into broader lexical-grammatical structures. Each instance of a simple verb (e.g., *jazdy* – “wrote”) is represented as an individual within the ontology, enabling precise semantic reasoning. Logical axioms formalize subclass hierarchies, supporting automated classification and inheritance of features. This design facilitates the systematic identification of verb types and their usage contexts, thereby contributing to the development of grammar-aware learning technologies (Figure 4).

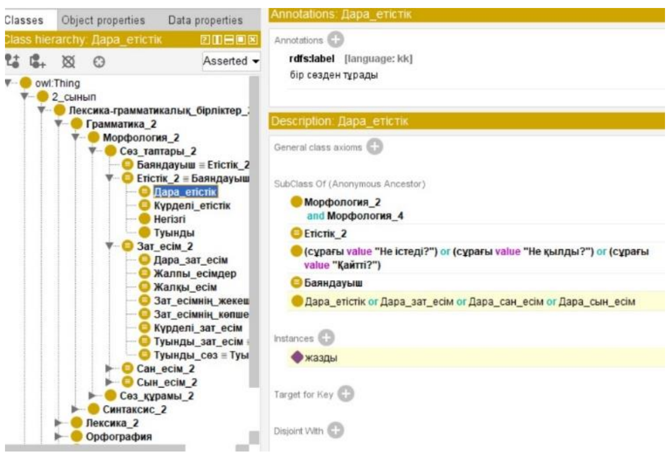


Figure 4. Concept “simple verb”

The ontology also supports the unification of Kazakh language educational content for primary school. By linking lexical and grammatical units with explanatory elements, it enables automated processing of textbook materials, the generation of grammar and vocabulary tasks, and the design of individualized learning pathways.

Furthermore, the ontology captures key semantic relations, including antonymy, synonymy, and hyponymy. For example, in Figure 5 the object property *antonimı* (antonym) defines a link between words with opposite meanings, described as "*tılımızdegı mağynasy qarama-qarsy sözder*" ("words with opposite meanings in our language"). These semantic relations are crucial for interpreting meaning in context and for supporting intelligent applications capable of analyzing and generating coherent Kazakh texts.

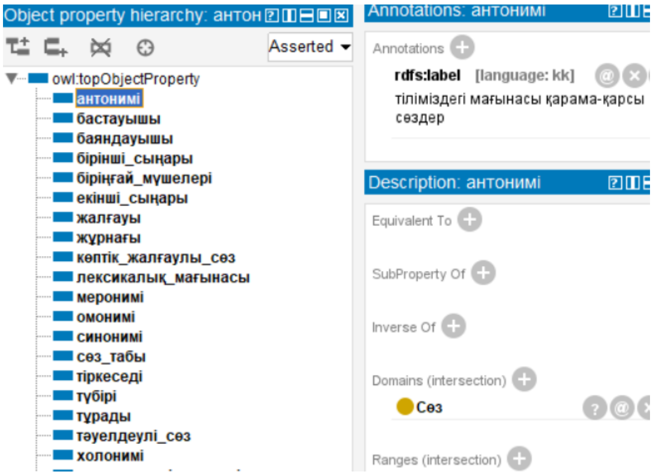


Figure 5. Fragments of object properties

By complementing the semantic properties of objects, the ontology integrates data properties that reflect specific attributes of lexical units. For example, the property "*bolady*" (can be/has) encodes grammatical features such as syntactic roles, punctuation marks, or associated morphological forms. These data properties are necessary for representing the rules and patterns of the Kazakh language, enabling automated reasoning and content generation on educational platforms (Figure 6).

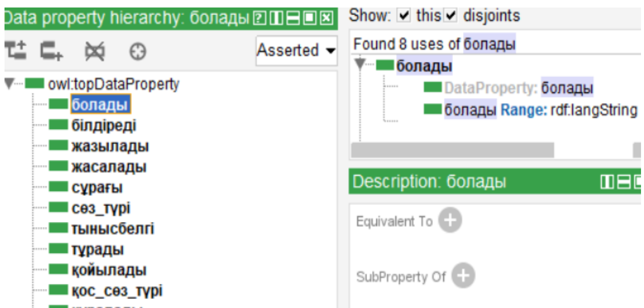


Figure 6. Representation of the data property "bolady" and its related attributes used to define lexical and grammatical features of terms in the ontology

From a lexical perspective, ontology reflects both word meanings and word-formation processes. This facilitates the identification of semantic characteristics of lexical units. As illustrated in Figure 7, the word *körıktı* (beautiful) is defined as a synonym of *ädemı* (charming), exemplifying how the ontology formalizes semantic equivalence between terms.

Explanatory terms are modeled as key elements of textual and verbal communication, structuring language knowledge in terms of its practical use in communicative contexts. For example, within the ontology, the term *mätın* (text) is classified as an explanatory term. Its definition is given through annotations, and different text types are represented as subclasses. The relationship between a text and its title is expressed through equivalence, with the presence of a title considered an essential property of a text in this ontological structure (Figure 8).

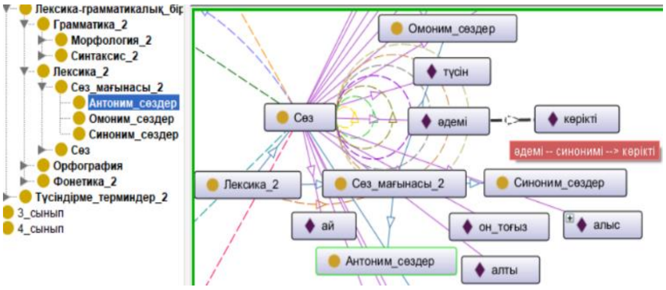


Figure 7. Visualization of synonymic relationships in the ontology

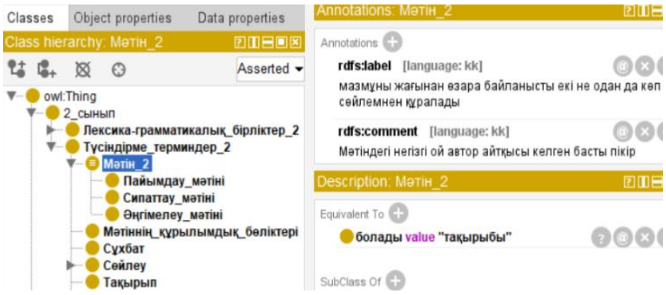


Figure 8. Ontological representation of the concept "*Mätın*" (Text)

A key challenge in developing the ontology was ensuring alignment of terms across multiple grade levels, such as between Grade 2 and Grade 4. This was addressed by modeling intersections of grammatical levels, allowing the ontology to capture both continuity and the increasing complexity of language mastery expected at successive stages of education.

Furthermore, using descriptive logic (DL) queries allows for the automatic identification of specific grammatical features. For example, words containing plural forms can be extracted, as shown in Figure 9. This functionality is based on linguistic data encoded in the ontology and supports the detection of plural suffixes, thereby improving the semantic processing of grammatical rules in educational applications.

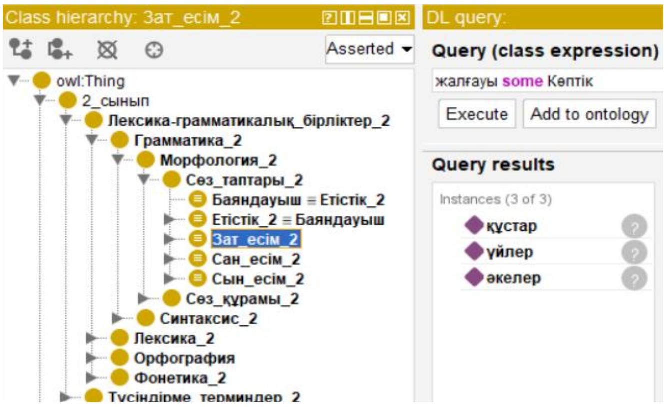
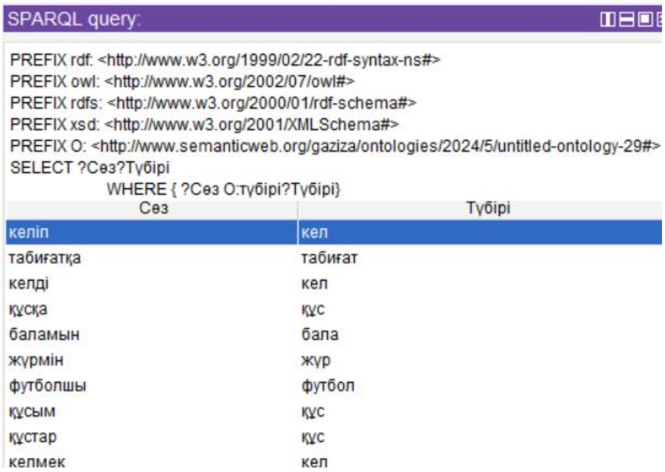


Figure 9. Identification of plural form words using a descriptive logic (DL) query

Figure 10 illustrates the extraction of a root morpheme (stem) from the linguistic database using a SPARQL query. This method enables the analysis of word structure by identifying its morphological components, particularly the root to which affixes are attached.

By integrating SPARQL queries into the ontological model, the system functions not only as a repository of linguistic data but also as a tool for intelligent processing. This functionality is particularly useful for tasks involving automatic word parsing and morphological analysis in educational contexts. In addition, it enhances the understanding of word-formation mechanisms and supports the creation of adaptive learning tools for teaching Kazakh morphology.

In summary, the integration of SPARQL queries for automatic root morpheme extraction significantly expands the system's capabilities for intelligent processing of linguistic data. This functionality makes the ontology a valuable resource for teaching and learning Kazakh language morphology, while supporting adaptive and data-driven educational approaches.


SPARQL query:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX O: <http://www.semanticweb.org/gaziza/ontologies/2024/5/untitled-ontology-29#>
SELECT ?Сөз?Түбірі
        WHERE { ?Сөз O:түбірі?Түбірі}
```

Сөз	Түбірі
келіп	кел
табиғатқа	табиғат
келді	кел
құсқа	құс
баламын	бала
жүрмін	жүр
футболшы	футбол
құсым	құс
құстар	құс
келмек	кел

Figure 10. Root extraction of words via SPARQL query

The selected models were adopted for their suitability for analyzing competencies, ensuring consistency in learning outcomes, and providing accurate assessment results. Compared to alternative methods, these models provide transparency, robustness to incomplete educational data, and flexibility in integrating ontological structures. Traditional statistical approaches were deemed insufficient, and deep learning methods were excluded due to their "black box" nature. Overall, the selected models adhere to the principles of competency-based assessment and are suitable for integration into real-world educational environments.

4. RESULTS

4.1 Demonstration of the system functionality

The functionality of the developed ontological learning platform was tested through a series of controlled user interaction scenarios. During the pilot phase, a demonstration of the chatbot's operation was conducted, based on an ontological model that provides semantic analysis and automated interactive evaluation of student responses.

Figure 11 illustrates an example of a typical interaction scenario in which the system formulates the question: "What part of speech is the word 'wrote'?" The student enters the answer through the interface, after which the semantic analysis module, based on the ontology, classifies the task as grammatical and automatically checks the correctness of the answer.

Two typical cases of interaction were identified:

- Case A (correct answer): When the student answers, "It's a verb," the system generates positive feedback: "Correct! The word 'wrote' is indeed a verb."
- Case B (incorrect answer): When answering "It's a noun," the system automatically generates a correction message: "Incorrect. The word 'wrote' is a verb, since it denotes an action."

This interaction scheme demonstrates the implementation of dynamic feedback, in which students receive immediate feedback on their answers, explanations of errors, and the opportunity to re-attempt the task. This mechanism promotes the development of conscious grammar skills and increases motivation for learning.

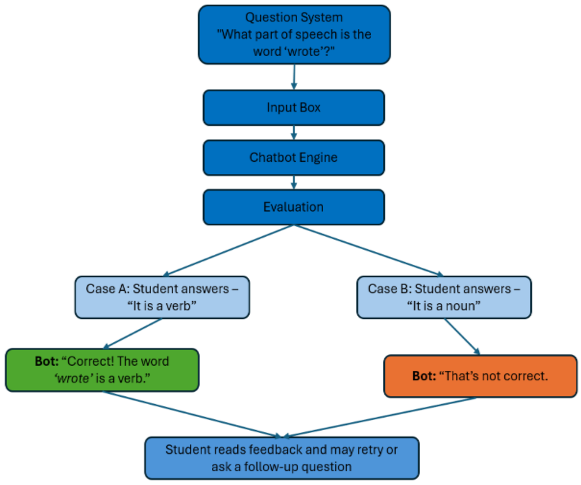


Figure 11. Ontology-based chatbot interaction flow for grammar question evaluation

The ontological learning system was tested in a twelve-week experiment involving 200 students in grades 2–4. Throughout the entire experiment, the system demonstrated stable operation, correctly identified student responses, and generated semantically sound feedback in accordance with the established ontology rules.

The results showed a consistent increase in scores across all six language competencies, indicating that ontologically guided reasoning can effectively support the acquisition of the Kazakh language at the primary level.

4.2 Experimental evaluation in a school setting

Following successful testing of its functional characteristics, the system was implemented in a real-life educational environment at a comprehensive school in Astana, Republic of Kazakhstan. The study involved 200 primary school students (grades 2–4), representing a typical sample of students in this age group.

The ontological platform was used in Kazakh language lessons and aimed to develop six key aspects of language literacy: vocabulary, grammar, spelling, reading, writing, and text comprehension. Thus, the experiment covered both receptive and productive language skills.

The pilot study lasted twelve weeks, with lessons held twice a week, 40–45 minutes each. The ontological system was implemented in a natural learning environment, without disrupting the existing curriculum structure. Teachers acted not only as observers but also as active facilitators, guiding students through the chatbot, directing their attention to grammatical patterns, and encouraging conscious language use.

To assess learning effectiveness, standardized pre- and post-tests, developed in accordance with the national curriculum, were used before and after the experiment. The system provided dynamic feedback, allowing students to instantly receive information about the correctness of their answers, analyse errors, and independently adjust their learning strategies.

According to teachers, the implementation of the ontological platform has contributed to increased learning motivation, the development of independence, and increased student engagement in the classroom. Furthermore, an improvement in the quality of language interaction was noted: students began using the digital interface more frequently for self-assessment and reinforcement of their learning.

The obtained data confirm that the use of an ontologically controlled learning system is effectively integrated into traditional school practice, ensuring the growth of linguistic competence and an increase in the cognitive activity of students.

4.3 Descriptive and statistical results

Descriptive and statistical results by class and gender.

To assess how well the ontological learning platform performed, the results were examined in detail, taking into account differences across both grade levels and gender. The study involved 200 primary school students (grades 2–4) from a school in Astana, 99 girls and 101 boys. The analysis covered six key competencies: vocabulary, grammar, spelling, reading, writing, and text comprehension.

Table 2 presents the results obtained for second-grade students ($n = 65$). The analysis revealed a steady increase in scores across all language areas. Girls demonstrated greater improvement in spelling and writing, while boys demonstrated greater improvement in grammar and text comprehension.

Table 2. Comparative analysis of the growth of language competencies in second-grade students

Competence	Girls (n = 34) Δ%	Boys (n = 31) Δ%	P-Value	Cohen's d	Interpretation
Vocabulary	+16.5	+15.9	<0.05	0.41	Moderate effect
Grammar	+17.2	+19.5	<0.05	0.48	Average effect
Spelling	+15.8	+13.4	<0.05	0.39	Minor difference
Reading	+14.1	+13.6	<0.05	0.28	Minor difference
Writing	+15.9	+13.8	<0.05	0.33	Average effect
Understanding the text	+15.5	+16.4	<0.05	0.30	Uniform progress

The analysis revealed statistically significant improvements across all competencies ($p < 0.05$). The largest gains were observed in grammar (+18.3%) and vocabulary (+16.2%), reflecting the early development of basic language skills.

Table 3 presents the results obtained for third-grade students ($n = 68$). Analysis showed that the gains in scores were more balanced than in other grades. Girls demonstrated higher scores in reading and writing, while boys demonstrated higher scores in grammar and text comprehension.

Table 3. Comparative evaluation of language competency development among third-grade students

Competence	Girls (n = 33) Δ%	Boys (n = 35) Δ%	P-Value	Cohen's d
Vocabulary	+17.9	+16.4	<0.01	0.42
Grammar	+18.4	+19.1	<0.01	0.51
Spelling	+16.3	+15.1	<0.05	0.36
Reading	+18.8	+17.5	<0.01	0.47
Writing	+19.3	+16.8	<0.01	0.52
Understanding the text	+18.5	+19.4	<0.01	0.49

The average increase was approximately +18.0–19.0%, with statistically significant differences across all categories ($p < 0.05$). The Cohen's d values ranged from 0.36 to 0.52, indicating a moderate effect.

Table 4 presents the results obtained for fourth-grade students ($n = 67$). The analysis revealed the most pronounced improvement compared to other grades. Girls demonstrated greater improvement in writing and vocabulary, while boys showed higher gains in grammar and spelling.

Average Cohen's d values were around 0.45–0.50, indicating a moderate effect of the implemented ontological platform.

To ensure a comprehensive presentation of results across all levels of education, a consolidated comparative analysis was conducted, combining data across three grades. The final values are presented in Table 5, which reflects the dynamics of average gains, the range of statistical significance, and the nature of the pedagogical effect.

Table 4. Changes in language competency indicators among fourth-grade students by gender

Competence	Girls (n = 32) Δ%	Boys (n = 35) Δ%	P-Value	Cohen's d
Vocabulary	+17.9	+16.4	<0.01	0.42
Grammar	+18.4	+19.1	<0.01	0.51
Spelling	+16.3	+15.1	<0.05	0.36
Reading	+18.8	+17.5	<0.01	0.47
Writing	+19.3	+16.8	<0.01	0.52
Understanding the text	+18.5	+19.4	<0.01	0.49

Table 5. Summary analysis for all grades

Grade	Average Growth (%)	Average Cohen's d	P-Value Range	Characteristics of the Effect
2nd grade	+16.5	0.87	<0.05	Moderate effect
3rd grade	+18.8	0.94	<0.01	Moderate to strong effect
4th grade	+21.0	1.12	<0.001	Strong effect

To summarize the data obtained and compare results across classes and gender groups, an integrated analysis of student performance dynamics was conducted. This stage of the study not only confirmed the effectiveness of the implemented ontological platform at different educational levels but also identified the specifics of its impact depending on the age and gender of students.

Table 6. Average results (in % of the maximum possible score) before and after the implementation of the platform

Grade	Gender	Pre-Test Mean (%)	Post-Test Mean (%)	Growth (%)	P-Value	Cohen's d
2nd grade	Girls (n=34)	61.2	77.4	+16.2	<0.05	0.86
	Boys (n=31)	59.8	76.5	+16.7	<0.05	0.88
3rd grade	Girls (n=33)	63.4	82.2	+18.8	<0.01	0.95
	Boys (n=35)	62.7	81.4	+18.7	<0.01	0.93
4th grade	Girls (n=32)	65.8	86.5	+20.7	<0.001	1.10
	Boys (n=35)	64.9	86.2	+21.3	<0.001	1.14

Table 7. Statistical summary of pre-test and post-test results across competencies (overall sample, n = 200)

Competency	Pre-Test Mean (%)	Post-Test Mean (%)	SD	Mean Diff	t	df	95% CI	Cohen's d
Vocabulary	62.1	78.3	8.5	16.2	5.12	199	[12.1 – 20.3]	0.86
Grammar	63.0	80.8	8.9	17.8	5.45	199	[13.4 – 22.2]	0.91
Spelling	61.5	76.9	7.8	15.4	4.98	199	[11.6 – 19.2]	0.82
Reading	62.7	78.9	8.1	16.2	5.08	199	[12.0 – 20.4]	0.85
Writing	63.3	79.5	8.3	16.2	5.10	199	[12.2 – 20.2]	0.87
Text comprehension	62.9	79.8	8.7	16.9	5.30	199	[12.8 – 21.0]	0.89

Summary statistics are provided in Table 6. The table presents the average pre-test and post-test scores expressed as a percentage of the maximum attainable score, along with the corresponding gains, the statistical significance levels (p-values), and the effect sizes (Cohen's d).

Pre- and post-test results indicate statistically significant increases across all grades and both gender groups. The largest gains were recorded for fourth-grade students, where the average overall score increased by approximately 21%, with a large effect size ($d > 1.1$). In third grade, there was a steady improvement in text comprehension and writing (an increase of approximately 19%), while in second grade, there was a strengthening of basic language skills-vocabulary and grammar (an increase of approximately 16%). Differences between girls and boys were minimal across all grades, indicating a consistent pattern of improvement in both groups.

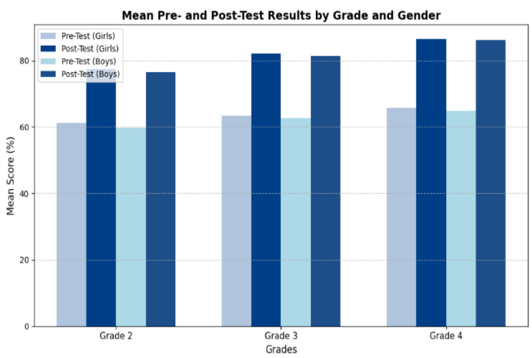


Figure 12. Mean pre- and post-test results by grade and gender

The graphics presented in Figures 12 and 13 allow visualizing the identified trends and confirm the statistical conclusions drawn during the analysis. The graphs demonstrate a steady increase in indicators across all grades and gender subgroups, and also confirm the absence of significant differences between the results of girls and boys. The most pronounced positive dynamics are observed among fourth-grade students, which correlates with the results presented in Tables 4-6 and indicates the cognitive maturity of this age group. Thus, the data visualization provides further confirmation of the effectiveness of the implemented ontological learning platform and its potential to support adaptive language learning in elementary school.

Analysis of the data presented in Figures 12 and 13 reveals a steady improvement in academic performance across all grades and gender groups. Average scores show a steady increase from second to fourth grade, indicating the progressive development of language competencies and demonstrating the positive impact of integrating the ontology-based learning platform into the educational process.

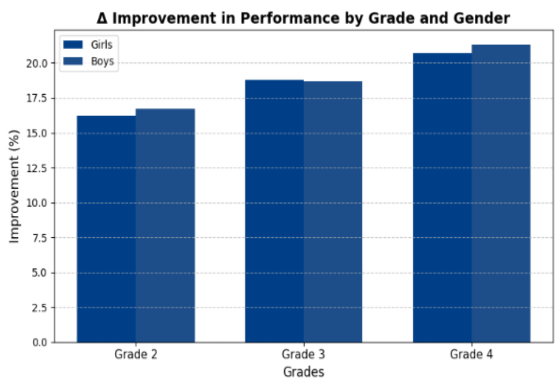


Figure 13. Δ Improvement in performance by grade and gender

The largest gains were observed among fourth-grade students. The combined increase in six language competencies exceeded 20%, indicating a link between students' cognitive development and their ability to consciously apply linguistic knowledge.

Table 7 provides a detailed statistical summary of pre-test and post-test results across all competencies. The results confirm statistically significant improvements, supported by t-test values, confidence intervals, and effect sizes.

A comparative analysis by gender revealed no statistically significant differences between the results of girls and boys.

This demonstrates the balanced pedagogical impact and versatility of the proposed approach. The obtained data are consistent with the statistical results presented in Tables 4-6 and confirm that the developed ontological system promotes the development of holistic language skills, cognitive activity, and academic independence in primary school students.

5. DISCUSSION

This study aimed to develop and test an ontology-based model for teaching the Kazakh language in primary school. The results indicate that organizing learning content through semantic structures can improve both the presentation and understanding of educational material. The comparison of pre-test and post-test results showed consistent improvements across all language competencies.

These findings are generally consistent with previous studies on the use of ontologies in education [16, 18], which also report positive learning outcomes. At the same time, this study focuses specifically on the Kazakh language and applies the approach in a primary school context. The results suggest that structured semantic models can support the development of language skills and enhance learners' understanding.

For RQ1, the analysis showed that nouns, verbs, adjectives, and basic sentence structures are the most important elements at the early stage of learning. These components formed the foundation of the ontology and were aligned with the school curriculum.

For RQ2, the study identified several types of relationships in the ontology, including hierarchical (e.g., class–subclass), associative (e.g., synonym, antonym), and explanatory links. These relationships help represent language knowledge in a structured and accessible way for learners.

For RQ3, students who used the ontology-based system showed improvements in all six language competencies, especially in grammar, vocabulary, and text understanding. This suggests that such systems can support individualized learning and provide structured feedback to students.

The observed learning gains can be linked to specific mechanisms of the system. Improvements in grammar can be associated with immediate semantic feedback, which allows students to identify and correct errors in real time. Gains in vocabulary and text comprehension are likely supported by the structured organization of linguistic concepts within the ontology, which helps learners understand relationships between words and meanings. In addition, the task sequencing mechanism, based on student performance, enables targeted practice, reinforcing previously learned material and addressing individual difficulties. Together, these features provide a coherent explanation of how the system contributes to the observed improvements.

The more pronounced improvement observed among fourth-grade students can be explained by both cognitive and pedagogical factors. At this stage, learners typically demonstrate a higher level of metalinguistic awareness and are better able to consciously apply grammatical rules and semantic relationships. In addition, the ontology-based system relies on semantic reasoning and structured feedback, which require a certain level of cognitive development to be fully effective. As a result, older students are more capable of benefiting from feedback based on their performance and concept-based task design, leading to stronger learning gains compared to lower grades.

From a teaching perspective, the use of ontology-based materials can help students become more independent and aware of language structures. It can also support teachers by making it easier to identify common mistakes and guide students more effectively.

However, several limitations should be noted. First, the study did not include a control group, so the results cannot be interpreted as a clear cause-and-effect relationship. The improvements may also be influenced by other factors, such as normal learning progression or teacher support. Second, the experiment was relatively short, and the model currently focuses only on text-based materials.

Future research should include a control group, extend the duration of the study, and explore the use of audio and visual data. This would allow a more complete evaluation of the approach.

Overall, the results indicate that ontology-based methods represent a promising direction for the development of digital tools for language learning.

6. CONCLUSION

The study provides preliminary evidence that the ontological approach may be effective for teaching Kazakh at the primary school level. The resulting ontology, based on educational materials for grades 2–4, shows potential pedagogical value and indicates that formalized semantic modeling can facilitate the structuring of educational content and support the development of language skills.

The results of an experiment involving 200 students from Astana schools showed statistically significant improvements in all six language skills-vocabulary, grammar, spelling, reading, writing, and text comprehension. The average improvement ranged from 16% to 21%, while the corresponding Cohen's d values fell between 0.39 and 1.14, indicating effect sizes from moderate to large. These findings suggest a positive pedagogical impact of the proposed platform, although further studies are needed to confirm its effectiveness.

To our knowledge, this study presents one of the first curriculum-aligned ontology-based models for Kazakh language learning, implemented within a digital learning platform. The model provides an interpretable link between linguistic categories, learning objectives, and digital learning tools, making it applicable to both automated learning systems and traditional school practices. The study's practical contribution is that the system can support:

- creation of digital textbooks and online courses on the Kazakh language;
- creation of a unified digital database of educational terms and concepts;
- improvement of the quality of pedagogical diagnostics and individualized learning;
- development of national educational platforms that support bilingual education and digital transformation of schools.

Despite the positive results, the study has certain limitations. The study did not include a control group, which limits the ability to draw causal conclusions. The observed improvements may also be influenced by other factors, such as normal learning progression or teacher effects. In addition, the model relies primarily on text data and requires further development to incorporate multimodal components (audio, visual data, speech corpora). Furthermore, the duration of the experiment (twelve weeks) limits the ability to assess long-term effects. Promising areas for future research include:

- expanding the ontology with speech and contextual data;
- integration with automatic speech analysis and machine translation systems;
- conducting long-term experiments to evaluate the sustainability and scalability of the results;
- development of cross-disciplinary versions of the platform for other subject areas.

Overall, this work suggests that ontological methods can be a useful and promising tool for digital linguodidactics, supporting structured and culturally relevant language learning.

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INFORMED CONSENT STATEMENT

Informed consent was obtained from the parents or legal guardians of all participating students prior to the study. The research was conducted with the approval of the school administration and in accordance with ethical standards for research involving minors. Participation was voluntary, and all data were anonymized to ensure the privacy and confidentiality of the students. The study was carried out in a regular classroom setting as part of the standard educational process.

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