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RESEARCH ARTICLE

Opportunities for Developing Natural Language Models in Building Artificial Intelligence Systems to Enhance Educational Process Support

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ABSTRACT

This article is dedicated to analyzing the problem of creating artificial intelligence (AI) systems that enable logical and hardware-level modeling of solutions described by mathematical operations based on natural language (NL), which form elements of the structural organization of information-intellectual technologies. The article presents a concept for organizing artificial intelligence, as well as intelligent support for educational processes, particularly in higher education institutions. The research utilized a comprehensive approach that combined desk research with analysis of scientific literature and expert surveys. In the discussions of the research findings, inductive reasoning was employed to allow for general conclusions. The article concludes that one of the most suitable areas for working with data and knowledge represented by language models is intelligent support for educational processes in higher education institutions.

INTRODUCTION

In the 20th century, a material-energy and socio-economic crisis in public production emerged, which was resolved by economically developed countries shifting from material-energy production and consumption technologies to information-intellectual technologies, where material-energy resource savings are achieved through the transition from information processing to knowledge processing (Akhmetshin et al., 2018; Abdullaev et al., 2023; Ukolova and Afanasyev, 2023)

At the turn of the 21st century, the topics of intelligent systems and intelligent support in higher education have undergone significant changes (Filipova, 2024; Aboimova et al., 2024). There has been a clear positive trend towards perceiving intelligence as a characteristic property of systems with high organizational complexity (Mukhametgaliyeva et al., 2024), a property that is quite specific and sufficiently expressive only in context-dependent languages (Shumakova et al., 2023). Another beneficial trend is the gradual recognition among researchers that the von Neumann computer architecture, essentially a finite automaton, cannot serve as a tool for creating intelligent systems because it is a context-independent system (Zotov, 2022).

This has given rise to a new scientific direction asserting that as one moves up the hierarchy, the intelligence of a system increases while its precision decreases, and vice versa (Yahya et al., 2021). Such systems are designed to operate in conditions of uncertainty (the inability to precisely mathematically describe) the information about the properties and characteristics of systemically complex objects and their environment (Pullmann et al., 2017; Elmorsy et al., 2025).

In real systems working under high uncertainty conditions, the construction of intelligent systems (artificial intelligence, hereinafter referred to as AI) inevitably requires the use of new information technologies oriented towards streams of context-dependent information, i.e., the highest levels of system complexity (Hoppe et al., 2017; Begishev et al., 2024), and the capability to build structures that implement objects that are incalculable in the conventional sense, one of which is human speech or natural language (NL) (Giustozzi et al., 2018).

LITERATURE REVIEW

According to (Dou et al., 2020), NLP (Natural Language Processing) is a branch of AI focused on developing methods for formally describing natural language (NL) and representing the knowledge embedded in texts. The primary goal of NLP research in AI systems is to create models that describe language structure and explore the mechanisms for understanding and formulating statements (Batura, 2016).

Ensuring interaction with AI in NL is a critical task for AI research. Databases, application software packages, and expert systems based on AI need to be equipped with flexible interfaces for numerous users who prefer not to interact with computers in artificial languages (Marchuk, 2007).

NLP systems can be divided into two categories:

- systems that facilitate the use of other programs (e.g., NL interfaces for programs like operating systems or databases) (Hirschberg and Manning, 2015),
- systems designed to perform specific operations on NL texts (e.g., determining keywords based on content or summarizing text) (Sun et al., 2017).

The process of NL communication is based on complex mechanisms related to the perception and production of statements. Researchers identify the following levels of NL analysis (Hobson et al., 2020) :

- Acoustic – rhythm and intonation of language (e.g., testing voice modulation can help determine the speaker's emotions),
- Phonetic – study of the language's sound structure (elementary sounds, or phonemes, with an international phonetic alphabet similar to the textual alphabet),
- Morphological – studying word structure (roots, endings), providing grammatical interpretation for individual words in text (in the simplest case, identifying the part of speech, with additional cases including word form, such as case, gender, and number for nouns),
- Syntactic – grammatical analysis of sentences (language grammar defines word combination rules, allowing for the verification of sentence structure),
- Semantic – describing the meanings of words and sentences (semantic analysis can check logical correctness, e.g., "The dog reads a newspaper"),
- Pragmatic – examining meaning based on the statement's context (e.g., anaphora, where pronouns are linked to text elements, such as "Peter bought a bike. It is gray").

The main challenges of NL analysis include natural language complexity (rich vocabulary, diverse grammatical structures), syntactic ambiguity of words, semantic ambiguity (a major issue in machine translation, where context determines the correct word meaning), syntactic ambiguity at the phrase or sentence level (allowing for different grammatical interpretations), issues with anaphoric references, the scope of quantifiers and negations, and unknown words (it is challenging to create a dictionary that covers all words, particularly names and geographical terms) (Yurgel, 2019).

Thus, the central issue for both general and applied NLP lies in addressing such ambiguities by transforming the external representation of NL into an internal structure, which requires a set of real-world knowledge (Maximov et al., 2016).

Applied NLP systems have an advantage over general systems since they operate within narrow subject areas. However, creating systems capable of communicating in NL across broader domains is possible, though current results remain far from satisfactory (Durnev et al., 2019).

Researchers predict further AI development, expecting that interaction with AI will ultimately lead to the realization that such information machines must function in a continuous mode of information acquisition and restructuring, resulting in an understanding of AI as an inherently dynamic system (Doherty and Wilson, 2019).

Based on the above, there is a need to develop a new concept for AI construction grounded in natural language principles.

The primary aim of this work is to outline a new concept of AI construction based on natural language principles and its potential to provide intelligent support for educational processes, particularly in higher education institutions.

MATERIALS AND METHODS

This article employs a comprehensive methodological approach that combines desk research and survey methods. In line with the research objective, the article attempts to provide the most complete characterization of the levels of natural language (NL) analysis for building an AI system based on natural language principles and to determine the capabilities of an AI system built on these principles in supporting educational processes. The study addresses the following research questions:

1. What are the main applications of an AI system built on natural language principles for intelligent support in educational processes?

2. What advantages arise from using an AI system based on natural language principles in the educational process?

To develop a comprehensive understanding of current knowledge on NL analysis, the desk research method was used. This method allowed for an in-depth review and analysis of scientific literature on the research problem, a detailed characterization of the levels of NL analysis for building an AI system, and a thorough overview of current trends and research in this field.

To answer the research questions, an expert survey method was utilized. A sample size of 45 experts was determined sufficient for the study. These experts, who met the criterion of having at least three publications on the research problem in peer-reviewed journals, were invited via email to participate in the survey. Of those contacted, 41 agreed to participate, and responses to the research questions were obtained through subsequent email correspondence. The results were processed to determine the rankings and weights of the primary applications and advantages of using an AI system based on natural language principles in higher education.

For a more objective analysis of the data obtained from the expert survey, the consistency of expert opinions was measured using Kendall's concordance coefficient, which provided a mathematically processed evaluation of the results (Shabalina et al., 2024).

RESULTS

Levels of Natural Language Analysis (Results of Desk Research)

Phonetic Analysis. The task of phonetic analysis is to mathematically describe the letter-phoneme relationship, linking the sound of language in a specific phonetic context to the corresponding letter of the alphabet. Mathematical models of letter-phoneme relationships for vowels and consonants in Russian have been constructed in (Deryabina and Dyakova, 2011; Rama et al., 2009; Bartlett et al., 2008) based on formal descriptions of letter-phoneme rules using algebraic equations of finite predicates.

To create these models, grammatical features of phonemes are introduced, such as sound volume (vowel/consonant), vocalization (voiced/voiceless), velarization and labialization (small/medium/large), palatalization (hard/soft), nasalization (oral/nasal), and so on. Transitioning from phonetic features to the phonetic representation of sound forms a phoneme—a sign representing a class of sounds associated with a specific letter in the text. The reverse transformation allows replacing a phonetic symbol with a set of corresponding phonetic feature values of the sound. Procedures for such transformations are thoroughly developed and described in (Batura, 2016; Marchuk, 2007; Hobson et al., 2020; Boyarsky, 2013).

Through the description of letter-phoneme connections, a formal transition from the phonetic recording of a word to its graphic representation can be implemented in an intelligent interface (the task of phonetic analysis). Additionally, this enables obtaining phonetic transcription from an orthographic text (language synthesis task), as well as achieving system and structural synthesis of functionally oriented processors for language analysis and synthesis, which are essential components of AI systems.

Morphological Analysis. The task of morphological analysis is to identify word forms and assign each word form a set of morphological information (MI set). This set consists of morphological information strings (MI strings) structured as follows:

- number, <(stem or stem features), MI>, where the number is the sequential number of the word form in the phrase;
- stem (stem feature) is the semantic feature code, the number of the syntactic or semantic management model assigned to this stem in the stem dictionary;
- MI includes part of speech and grammatical categories: gender, number, case, tense, etc.

There are two methods for implementing morphological analysis (MA): dictionary-based (declarative), used for analyzing languages with limited inflection (e.g., English, French), and algorithmic (procedural), used for analyzing languages with extensive inflection, such as Russian. In MA, word forms are divided into stems and endings, both stored in dictionaries. MA is performed by searching for a particular dictionary stem and ending within the word form. Then, information about the stem and ending is compared to derive a complete morphological information set for the word form.

During MA, the variable part of a word form's ending is sequentially compared with dictionary endings. If a match is found, the matching segment of the word form is highlighted, yielding an acceptable stem (AS), acceptable ending (AE), and acceptable morphological information (AMI). Data on AE (AMI) are retrieved from the ending dictionary (morphological information), after which the search continues for other AE, AS, and AMI.

In the second step of word form analysis, the possible stems are identified by checking the convergence of obtained acceptable stems with the machine-readable dictionary of stems. In the third step, the information of the word form is compared with the acceptable stems and AEs verified by the stem dictionary.

Morphological Analysis Efficiency. The effectiveness of morphological analysis (MA) significantly depends on how machine dictionaries are stored in computer memory and the encoding method used. It is advisable to maintain a separate auxiliary dictionary of renumbered stems, arranged alphabetically and in single instances.

To represent grammatical category values for any word form, a 9-bit, 10-digit code can be used. Each digit in this code has a specific encoding purpose:

- r(1),r(2)r(1), r(2)r(1),r(2): part of speech of the word form,
- r(3)r(3)r(3): type and class of prepositions or animacy (for nouns or full adjectives),
- r(4i)r(4i)r(4i): verb person (1st-3rd),
- r(5)r(5)r(5): number (singular, plural),
- r(6)r(6)r(6): case,
- r(7)r(7)r(7): voice category (active/passive),
- r(8)r(8)r(8): tense (present, past, future),
- r(9)r(9)r(9): aspect (perfective/imperfective).

To create a single MI-string for an entire word form, the stem code and ending code are compared for matching in the first five digits. If there is no match, the data are incompatible, and a new ending code is selected for comparison. Once a match is found, the remaining digits of the resulting code are formed according to the rules of 10-digit disjunction of corresponding digits in the stem and ending codes. Additionally, operand convergence or a zero value check is performed.

This algorithm allows the interpretation of a variety of Russian flexion processes (analysis, synthesis, normalization, error correction, etc.) using canonical equations of the form Lϕ(X,Y)=1L\phi(X, Y) = 1Lϕ(X,Y)=1.

Syntactic Analysis. To "understand" a sentence in NL, it is essential not only to know the meanings of the words used but also to have information about their arrangement and relationships. The process of syntactic analysis, known as parsing, is carried out by a parser—a program that transforms linear text into a structure that conveys connections and dependencies between words and parts of a sentence.

The set of syntactic rules for a language is called its grammar. To define grammar, the concepts of an alphabet (a finite set of symbols in a language, represented by words in NL), a word (a finite sequence of symbols from the alphabet, which are sentences in NL) (Ybyraimzhanov et al., 2019), and a language (a set of words from a particular alphabet, where NL is a set of sentences) are introduced.

A critical issue is determining which sentences should be accepted by the grammar and which should be rejected. Each grammar must meet two criteria:

- It must generate all correct sentences of a language,
- It must generate only sentences of that language (it must not generate incorrect sentences).

Words in a language do not occur in random order, and the laws governing their arrangement are the subject of syntax. Syntax describes the structure of possible phrases and utilizes formal grammars, such as dependency trees, constituent structures, and augmented transition networks.

The decisive factor in choosing the correct grammar to describe syntax is the division of functions between the syntactic and semantic layers. Grammars typically analyze only the syntactic layer of a sentence (the so-called surface structure), while the "meaningfulness" of the sentence is addressed at the semantic level.

Thus, syntactic analysis uses pre-defined grammar templates to input phrases, aiming to establish a match between the analyzed sequence and meaningful syntactic structures.

Semantic Analysis. Semantics defines the relationships between signs and their concepts, providing the content or meaning of specific signs as a framework for context-dependent communication in complex systems.

The starting material for semantic analysis in NL is the syntactic structure of a phrase or its fragment, along with information on word meanings.

Semantic analysis can be broken down into three levels: describing the meanings of words, sentences, and texts. Its objectives may include:

- Verifying sentence correctness in terms of clarity and logic (e.g., filtering out illogical sentences),
- Resolving ambiguities in sentence structure (e.g., correctly interpreting words and selecting the appropriate grammatical structure),
- Determining a sentence's meaning representation for further analysis (e.g., describing sentence meaning for in-depth analysis).

Thus, the main task of semantic analysis is to resolve ambiguities, including morphological and lexical polysemy of word forms and syntactic structures of sentences.

Two approaches are used to describe semantics: the structural (relational) approach and the componential approach. The structural approach is based on the assumption that language units (sounds, words, etc.), identified during sentence analysis, can be given meaning based on their relationship to other units in the language system. The meaning of a word is then determined by its relations with neighboring (semantically close) and opposing words.

The componential approach suggests that meaning can be defined by breaking it down into simpler (elementary) semantic components. For example, the meanings of the words "man," "woman," and "boy" can be defined as follows: man = human + male + adult; woman = human + female + adult; boy = human + male + minor.

To analyze the semantics of an NL message, it is necessary to define the meanings of message units. Word meanings are classified according to a set of a priori features: action–instrument of action, or in other words, verb–noun in a particular case. Semantic networks and the associated mathematical apparatus are used to study the semantics of such phrase types.

Examples of semantic theories in NLP systems include semantic grammars and Schank's Conceptual Dependency (CD) theory. Semantic grammars combine the syntactic description of a sentence with its semantic information (e.g., context-free grammars, where non-terminal symbols represent specific semantic concepts). Semantic grammars are usually used in systems providing natural language access to databases. These systems are typically limited to a narrowly defined area, as expanding their scope would lead to a rapid increase in rules. The main advantage is the combination of syntactic and semantic analysis within a single formalism.

Schank's Conceptual Dependency (CD) theory uses the phenomenon of "conceptual" similarity of verbs. The structure representing information in a sentence is based on relationships between concepts that form the main elements of a given event, such as action, agent, object affected by the action, purpose, etc. This structure is called a CD formula.

In CD formula notations, simplifications are made regarding the naming of activities. For this purpose, so-called elementary actions were created, which serve the function of verbs in the formulas. Schank proposed eleven elementary actions. For example, the action MTRANS signifies the transfer/receipt of information, corresponding to verbs like "read," "speak," "hear," "see," "learn," "promise," etc. These actions can be divided into primary and auxiliary. Primary actions play a key role in the formula, representing the most characteristic action of the event. Auxiliary actions provide additional information, detailing the behavior of, for example, an object or tool.

Describing reality using CD formulas has two important features. First, the introduction of elementary actions generalizes the representation of NL sentences. If two different sentences describe the same event, they will use the same elementary action in the corresponding CD formulas. The second advantage of CD theory is the ability to include information in the formulas that is not directly reflected in the sentence's content but pertains to some general knowledge about the surrounding reality.

Levels of Natural Language Analysis (Expert Survey Results)

Table 1 presents the main applications of NLP systems that can be used to provide intelligent support for educational processes.

Table 1: Primary Applications of NLP Systems in Supporting Educational Processes

No.	Primary Applications	Rank	Weight
1	Speech recognition and synthesis	1	0.31
2	Human-computer dialogue	2	0.23
3	Text understanding and generation (e.g., intelligent information retrieval, document summarization, knowledge base creation)	3	0.16
4	Automatic text translation	4	0.14
5	Intelligent text editors (e.g., automatic error correction)	5	0.11
6	Foreign language learning	6	0.05

Note: Compiled based on an expert survey; the Kendall's concordance coefficient W=0.69 ($p < 0.01$), indicating strong consistency in expert opinions.

Table 2 presents an analysis of the advantages associated with using NLP systems in education.

Table 2: Primary Advantages of Using NLP Systems in the Educational Process

No.	Primary Advantages	Rank	Weight
1	Use of computers by individuals without special training	1	0.36
2	Speed (keyboard: 0.5 words/sec; professional typist: 1.5-2.5 words/sec; spontaneous speech: 2.5-3.6 words/sec)	2	0.28
3	Use of computers by individuals with disabilities (one of the earliest applications of speech processing and recognition was voice-controlled keyboards)	3	0.21
4	Freeing users' hands (enabling parallel tasks)	4	0.15

Note: Compiled based on an expert survey; the Kendall's concordance coefficient W=0.72 ($p < 0.01$), indicating strong consistency in expert opinions

DISCUSSION

As AI continues to advance, it is increasingly evident that the use of these intelligent systems could expand significantly if it becomes possible to work with AI directly using human language. Specifically, the ability to control AI in real time using ordinary voice commands and to input and output information through natural human speech would greatly enhance usability.

Current speech recognition technologies are not yet robust enough for broad application, but research is actively exploring the use of concise, multi-meaning words (procedures) to facilitate understanding. Present-day language recognition systems rely on collecting all available (and sometimes even redundant) information necessary to recognize words. Researchers believe that recognizing language patterns based on signal quality may be sufficient for recognition. However, even with small messages of normal speech, direct transformation of diverse real signals into linguistic symbols, the desired result, remains challenging.

Subject areas where it is most appropriate to work with data and knowledge represented by language models are those dominated by empirical knowledge, where the complexity of facts and descriptions precludes the use of mathematical language. This is especially true for intelligent support in educational processes within higher education institutions (Gapsalamov et al., 2020).

As computer systems continue to develop, it is increasingly clear that their usage could expand greatly (Akhmetshin et al., 2024; Revyakina et al., 2024) if it becomes possible to work with computers directly using human language. In particular, real-time voice control and the input and output of information through natural human speech would make these systems more accessible. The application of AI systems (Nikitenko et al., 2025) and the use of new technologies and methodologies related to computer systems (Polovchenko, 2024) will enhance the efficiency of educational process support (Vavilov et al., 2024).

CONCLUSION

For successful NLP recognition, the following tasks must be addressed: processing the dictionary (phonemic composition), syntax processing, language reduction (including the possible use of strict scenarios), speaker selection (including age, gender, native language, and dialect), speaker training, selection of a specific type of microphone (considering the microphone's directionality and placement), system operating conditions, and obtaining results with error indication.

Today, the only known objective bearer of knowledge and intelligence is the human being, while the medium of expression, external communication, and carrier of intelligence is human language, which will be the subject and focus of research in future studies.

AUTHORS' CONTRIBUTIONS

IA and KV conceived the idea, designed the project and wrote the manuscript. OT and AN participated in the design of the study and helped in writing the manuscript. VV edited the final draft and was responsible for project administration.

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