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USE OF SEMANTIC NEURAL NETWORKS IN VIRTUAL LEARNING ENVIRONMENT QUALITY ANALYSIS TASKS

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This article explores the possibilities and prospects of using semantic neural networks (SNNs) for analyzing the quality of virtual learning environments (VLEs), which has become increasingly relevant in the context of education digitalization. Semantic neural models such as BERT, RoBERTa, and GPT provide deep comprehension of educational content, enable the interpretation of logical-semantic relationships in texts, and uncover hidden patterns of perception and emotional tone in learning materials. The study defines key parameters that characterize VLE quality, including lexical richness, coherence, emotional polarity, and content relevance.

Special attention is given to applied analysis of student feedback, forums, and test materials, which are automatically processed by SNNs to assess teaching quality, course structure, and the level of interactivity. The author proposes a basic methodology for semantic analysis tailored to educational platforms, outlines the architecture of the model, and describes its training process based on specialized educational corpora.

The article examines both the advantages and limitations of integrating such models into higher education and the potential for embedding them into LMS systems and feedback support services. The practical value of the study lies in providing a scalable, objective, and efficient toolkit for assessing the quality of VLEs in order to improve the learning process.

Keywords*: semantic neural network; quality analysis; virtual learning environment; educational analytics; deep learning; natural language processing; cognitive technologies; distance learning.*

Statement of the problem. In today's environment of rapid development of distance learning and digitization of educational processes, there is an urgent need to develop new tools for assessing the quality of virtual learning environments (VLEs). Traditional analysis methods, which rely mainly on expert assessments, performance statistics, and questionnaires, do not provide sufficient depth, objectivity, and scalability of analysis, especially in conditions of large numbers of students, asynchronous interaction, and heterogeneity of educational content.

One promising area for improving VLE monitoring is the use of semantic neural networks (SNNs), which not only classify textual information but also identify meaningful relationships between content and user behavior. At the same time, the implementation of SNNs is accompanied by a number of challenges, particularly regarding the choice of architecture, data processing, quality assessment, and integration of results into the educational analytics system.

Currently, there is insufficient research on the practical implementation of SNN models for analyzing the quality of virtual learning environments, taking into account the specifics of educational content, the characteristics of online courses, and the need for feedback. The lack of a systematic approach complicates the creation of flexible, accurate, and understandable models. Thus, the problem arises of developing conceptual and applied foundations for building an SNN model for qualitative analysis of VLEs, which will contribute to the development of automated monitoring, course adaptation, and decision support on digital educational platforms.

Analysis of recent studies and publications. An analysis of recent studies and publications on the subject helps to outline the scientific context in which the research is developing. Many authors emphasize that semantic approaches are increasingly used not only in classical NLP tasks, but also in educational systems for monitoring, content analysis, and user interaction. Work [1] presents a virtual dataset, including automatic annotations (semantic augmentation) and a comparison of methods with a semantic component in VLEs. The authors directly link semantic analysis to virtual educational environments and show that adding semantics improves the quality of analysis. In studies [2], a neural network with attention mechanisms is used to predict student outcomes based on various factors of learning experience. The paper emphasizes the role of contextualization (through attention) in modeling the learning process, which brings us closer to the idea of SNN, which works with semantic connections between content and interaction. Article [3] discusses semantic network, clustering, and ANNs technologies for personalized learning, providing a historical basis for the application of semantic approaches in e-learning, which creates the prerequisites for modern SNNs.

Most studies focus either on big data analytics or content semantics, but do not combine both within a model integrated into VLE. There are few studies devoted specifically to semantic neural networks (SNNs) in the context of virtual learning environments. Also, many neural networks analyze but do not explain what semantic connections have been identified. Publications also lack standardized approaches to content quality metrics in VLEs with a semantic component.

As shown above, the scientific community has already accumulated considerable experience in the application of neural networks and semantic technologies in education. However, a systematic approach that comprehensively combines semantic content analysis, user behavior, and the quality of the learning environment in the form of an SNN model architecture for VLEs is rarely found. Our article aims to fill this gap by proposing methodological principles, model architecture, and evaluation methods that take into account the semantics of educational content and user interaction—that is, an integrated approach that is still underrepresented in the literature.

Purpose of the article. The purpose of the article is to study the possibility of using semantic neural networks in the tasks of comprehensive analysis of the quality of a virtual learning environment, with an emphasis on semantic processing of educational texts, communicative messages, and student feedback.

Presentation of the main research material. Over the past decade, there has been rapid development in distance learning. Educational institutions around the world have been forced or have strategically switched to using virtual learning environments (VLEs) [4], e-learning platforms, learning management systems (LMS) [5], massive open online courses (MOOCs) [6], and hybrid forms of teaching. On the one hand, this has significantly expanded access to education, but on the other hand, it has posed new challenges, particularly in terms of ensuring the quality of the educational process in a digital format.

In such conditions, traditional methods of assessing learning effectiveness based on statistical surveys, expert analyses, or manual content review are insufficient for scalable digital environments that generate large amounts of text data every day, from lecture materials to student comments in forums. As a result, there is an urgent need to implement the latest methods of intelligent data analysis, which allow not only quick but also in-depth interpretation of the informational context, emotional background, coherence of knowledge, and user feedback.

One of the promising technologies in this area is semantic neural networks—deep learning architectures capable of modeling and interpreting text content based on context, logic, and intonation. They are used in areas ranging from automated chatbots to public opinion analytics, and are now becoming increasingly important in the field of educational technology, where the quality of educational content and interaction with it is coming to the fore.

Despite the availability of numerous digital platforms and training courses, the question remains: how can the quality of the learning environment be assessed objectively, scalably, and flexibly without involving experts manually? Is it possible to create a tool that will automatically record not only technical indicators (attendance, test completion), but also the semantic quality of content, logical structure, coherence of knowledge, as well as the mood and needs of the user?

Traditional analytical tools are limited to lexical analysis or superficial assessment of emotional tone. At the same time, new-generation semantic models—such as BERT, RoBERTa, GPT, etc. – allow for the construction of more accurate predictive and analytical algorithms, the identification of hidden patterns in communications, the tracking of cognitive load, the identification of information gaps in courses, and the study of interactive communication between students, teachers, and the platform.

The object of the study is the virtual learning environment as a system of user interaction with digital educational content.

The subject of the study is the semantic analysis of text elements of the VLE using neural networks.

The following methods were used for the research: computational linguistics, machine learning methods, analysis of educational corpora, comparative evaluation of models, content analysis, and elemental analysis of feedback.

The scientific novelty of the research lies in the attempt to apply deep semantic models of neural networks specifically in the context of evaluating educational content, which goes beyond purely technical or lexical analytics. The paper proposes a proprietary methodology for evaluating the quality of VNS, which takes into account not only objective content parameters, but also the subjective experience of the user, expressed through emotional-semantic analysis.

The diagram in Fig. 1 illustrates the role of a semantic neural network (SNN) in the architecture of digital education. It demonstrates how SNN analyzes educational content and user behavior and generates feedback to improve the learning environment.

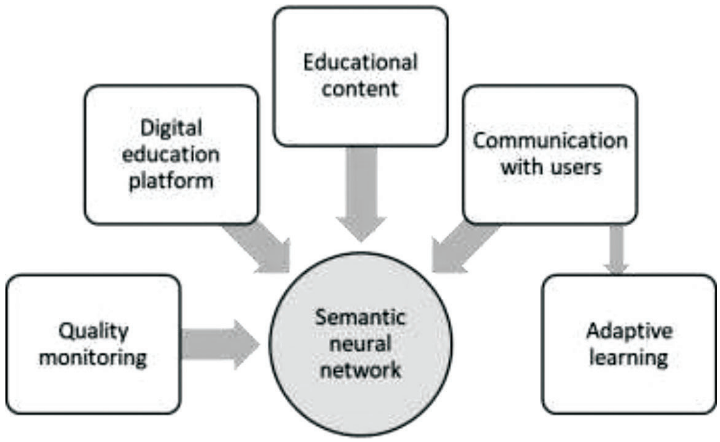

Fig. 1. The role of semantic neural networks (SNN) in the architecture of digital education

Semantic analysis in the context of digital education is considered a method of intellectual processing of textual, graphic, or audiovisual information that enables the recognition of meanings, the identification of hidden connections between concepts, and the structuring of knowledge. Its theoretical basis is semantic ontology, a formalized model that describes a subject area using concepts, attributes, and relationships between them.

In the field of virtual learning environments (VLEs), such technologies allow for a deeper analysis of the content of educational materials and the identification of semantic correspondence between the course objectives, user requests, and student activity. Among the key tools are semantic neural networks (SNNs), which mimic the human brain's ability to interpret meanings depending on context [8].

A semantic neural network is a type of artificial neural network designed to work with semantic information, not just structured data. It is capable of interpreting the meaning of words in context, performing thematic grouping, content filtering, and classifying educational resources according to semantic parameters.

Unlike traditional machine learning algorithms, SNN operates not only with statistical relationships between words or phrases, but also with a system of concepts—formally represented meanings and logical relationships between them. This allows it, for example, to assess the relevance of user queries to lecture content, recognize ambiguities in terms, filter out duplicates, and evaluate the completeness and relevance of content.

A virtual educational environment is a set of platforms, resources, and tools that enable interaction between teachers, students, and educational content. Semantic analysis of such an environment involves processing the following components: educational materials (lectures, presentations, videos, textbooks); user behavior patterns (number of transitions, reading time, scrolling depth, communicative activity); platform structure (sequence of modules, links between topics); feedback (forms, tests, surveys). [9]

Semantic neural networks in this context can act as an analytical module (Fig. 2) that automatically evaluates: the relevance of educational content to learning objectives; the dynamics of student understanding of terms and concepts; weaknesses in the course structure; the risk of cognitive overload or loss of interest [10].

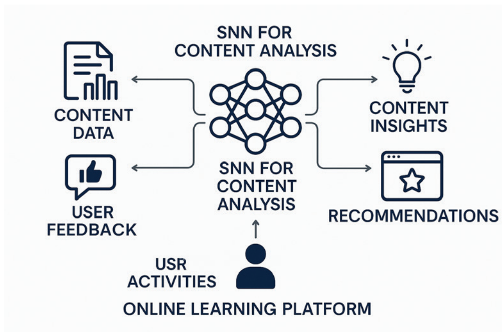

Fig. 2. Connections between components of the semantic neural network (SNN) system integrated into the distance learning platform

The following semantic analysis methods are used in digital education research: Latent Semantic Analysis (LSA) – a method that allows finding latent (hidden) connections between concepts in educational content; Word2Vec / FastText – vectorization models that construct a semantic space of concepts, allowing their proximity to be measured; BERT and GPT-like models – transformers that provide context-dependent analysis of the meaning of concepts in texts[13]; Knowledge Graphs + NLP – semantic graphs that structure knowledge in the form of nodes and relationships, integrated with natural language processing. Thus, these methods are used both for analyzing the qualitative parameters of content and for evaluating student interaction with the virtual environment, in particular: behavioral trajectories, semantic enrichment of the learning experience, and the level of individualization of learning.

Table 1 below presents a brief comparative description of the most common approaches to semantic analysis used to study the quality of virtual educational environments [12].

In summary, it can be argued that the use of semantic technologies, in particular semantic neural networks, in the field of virtual learning opens up wide opportunities for in-depth analysis of the quality of the educational process, identification of semantic gaps in content, and the formation of personalized learning trajectories. This allows us to move from traditional forms of assessment to intelligent adaptive analytics, where the result not only records the student's activity but also explains the reasons for success or failure based on the semantic context of their actions.

Table 1

Comparative characteristics of semantic analysis methods in virtual learning environments

№	Semantic analysis method	Main purpose	Typical architecture	Advantages	Restrictions
1	**Word2Vec / GloVe + SNN**	Analysis of similarity of concepts in educational texts	MLP / RNN with vectorization	Ease of implementation, speed, stability	Limited contextuality, does not take word order into account
2	**BERT, RoBERTa, DistilBERT**	Deep semantic processing of lectures, assignments, questions	Transformers with attention	High accuracy; understanding of context	Requires significant resources, complex configuration
3	**Autoencoder + SNN Clustering**	Clustering of educational content	Deep autoencoders	Identifying topics, grouping materials	Results are difficult to interpret; sensitivity to parameters
4	**Graph Neural Networks (GNN)**	Analysis of student actions in LMS, logs, interactions	GNN + semantic layer	Models user behavior well	Requires structured log data
5	**Recommendation SNN (Seq2Seq / Transformer)**	Generation of recommendations, construction of learning trajectories	Seq2Seq, RecSys Transformers	Personalization, semantic relevance	The need for large amounts of training data

Considering the practical aspects of building an SNN model for analyzing a virtual learning environment, we will describe the model architecture, select data for training, and methods for its evaluation.

The semantic neural network model, focused on analyzing educational content in VNS, is usually based on modern transformer architectures. Structurally, the SNN model consists of several functional modules, including: the Text Preprocessing Layer performs tokenization, cleaning, and normalization of educational text (e.g., lectures, assignments, forums); Embedding Layer, which uses contextual vector representations (e.g., BERT, RoBERTa, DistilBERT) that take into account the semantics of educational content; The Semantic Core Layer is a multi-level transformer structure for identifying connections between educational elements: topics, complexity categories, cognitive levels (according to Bloom's taxonomy), linguistic patterns, etc. Interpretation Block determines quality indicators: coherence, completeness, compliance with standards, readability, etc.; and finally, the Decision Layer module classifies or evaluates content on a quality scale, taking into account the context of user interaction (number of scrolls, reading time, participation in forums, etc.) [10, 13].

To train SNN models in the context of educational platforms, it is important to ensure the availability of a representative corpus of text and behavioral data. Such data includes: lecture materials (structured and unstructured PDF, HTML, DOCX);

descriptive elements of tests, assignments, courses; forums and chats in VLEs (Moodle, Canvas, Google Classroom, etc.); user activity log files; expert annotations that indicate deficiencies in content (manual labeling) [10]; quality indicators: readability, Flesch Index, thematic completeness, compliance with the course program. Data augmentation may include translation, synonym replacement, structure distortion (e.g., paragraph rearrangement) to increase the diversity of input examples.

The SNN model is trained in supervised or semi-supervised learning mode, depending on the amount of labeled data, in particular: loss function: categorical cross-entropy loss (Categorical Cross-Entropy); optimizers: Adam, AdamW; regularization methods: Dropout, Weight Decay; reinforcement learning: can be used to optimize the system's responses to user feedback.

To evaluate the quality of the semantic analysis model in the VNS, both classical classification metrics and interpretative indicators were used (Table 2).

Table 2

Metrics	**Purpose**
Accuracy / Precision / Recall	Classification standards
F1-score	Balance between precision and recall
ROUGE / BLEU	Semantic correspondence of the conclusion
Semantic Coherence Index	Assessment of the logical coherence of the text
Readability Index (Flesch)	Calculating text complexity
Coverage Ratio	Covering topics or learning outcomes
User Feedback Score	Indirect quality assessment based on reviews

Analyzing the possibilities of implementing the model, it can be argued that it can be implemented in PyTorch, TensorFlow, or HuggingFace Transformers environments using the following infrastructure: GPU/TPU computing; integration into LMS via REST API, JSON interfaces; quality monitoring using the TensorBoard or Weights & Biases platform [12].

The diagram of the architecture of the semantic neural network (SNN) model integrated into the distance learning platform reflects the sequence of data processing—from the collection of educational information to the analysis of the quality of user interaction (Fig. 3).

Figure 4 shows a diagram comparing educational environment analysis models – SNN, LSA, LDA, and BERT.

Analyzing the research results, we can conclude that SNN is the most comprehensive and context-sensitive approach, particularly effective in personalized learning and monitoring student interaction with VNS. LSA and LDA are statistical methods suitable for high-level thematic analysis, but they do not capture deep semantic relationships. BERT provides high quality thanks to powerful language representations, but without semantic structure (as in SNN), it may miss deep cognitive connections between elements of educational content.

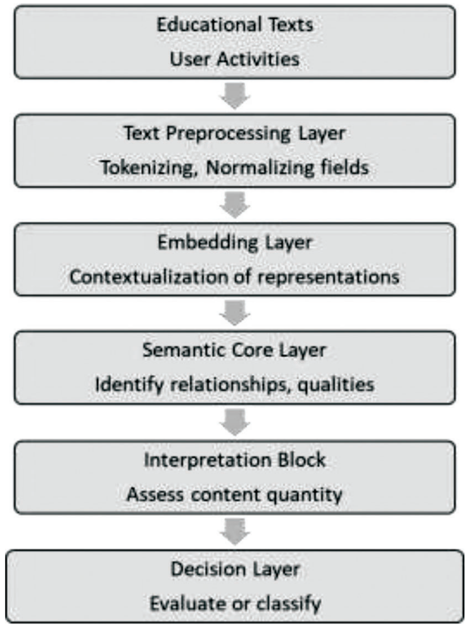

Fig. 3. Diagram of the architecture of the semantic neural network (SNN) model integrated into the distance learning platform

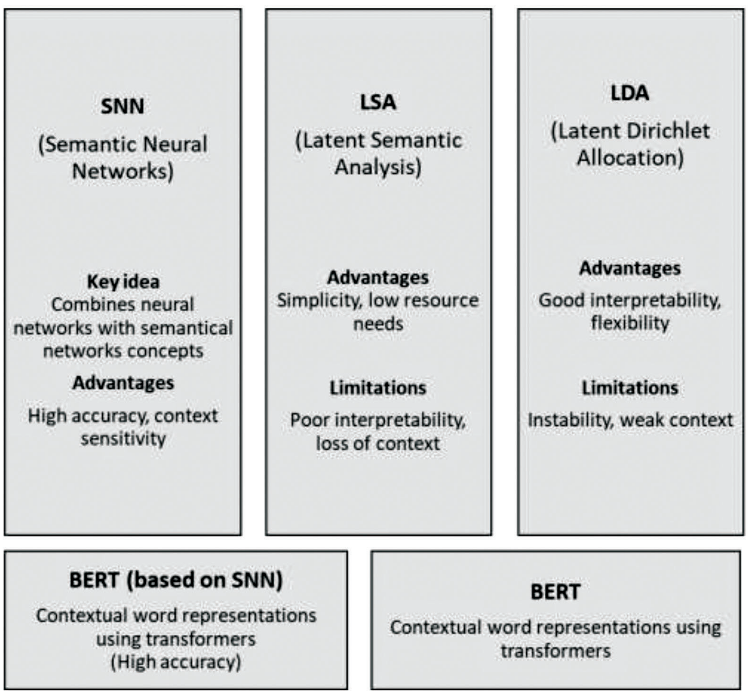

Fig. 4. Diagram comparing models for analyzing educational environments – SNN, LSA, LDA, BERT

Conclusion. Methods based on semantic neural networks demonstrate high efficiency in tasks related to in-depth content analysis, assessment of learning trajectories, development of recommendations, and monitoring of learning quality. At the same time, they require a well-thought-out data architecture, preliminary preparation of training corpora, and significant computing resources. The optimal approach is to combine several methods depending on the specifics of the data and the goals of the analysis.

The practical significance of the work lies in the applicability of the developed approach: for automated monitoring of the quality of online courses; support for adaptive learning; improvement of LMS with intelligent feedback; for analyzing the motivational, cognitive, and social aspects of interaction with the learning environment.

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ВИКОРИСТАННЯ СЕМАНТИЧНОЇ НЕЙРОННОЇ МЕРЕЖІ В ЗАДАЧАХ АНАЛІЗУ ЯКОСТІ ВІРТУАЛЬНОГО НАВЧАЛЬНОГО СЕРЕДОВИЩА

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У статті досліджено можливості використання семантичних нейронних мереж для оцінки якості віртуального навчального середовища (ВНС). Розглядаються теоретичні засади семантичного аналізу, архітектура нейронних мереж, специфіка параметризації освітніх даних. Проаналізовано приклади застосування нейромереж для виявлення змістових та емоційних характеристик освітнього контенту. Обґрунтовано перспективи інтеграції штучного інтелекту в автоматизовану оцінку освітнього середовища.

У роботі аргументовано можливості та перспективи використання семантичних нейронних мереж (СНМ) для аналізу якості віртуального навчального середовища (ВНС), що стає все більш актуальним у контексті цифровізації освіти. Семантичні нейромережі, зокрема моделі типу BERT, RoBERTa та GPT, забезпечують глибоке розуміння змісту навчального контенту, дозволяють інтерпретувати логіко-смислові зв'язки в текстах, виявляти приховані патерни сприйняття та емоційного забарвлення освітніх матеріалів. У статті визначено ключові параметри, що характеризують якість ВНС: лексична насиченість, когерентність, емоційна полярність та релевантність змісту.

Особлива увага приділена прикладному аналізу студентських відгуків, форумів і тестових матеріалів, що автоматично опрацьовуються СНМ для оцінки якості викладання, структури навчального курсу та інтерактивності взаємодії. Автором запропоновано базову методику семантичного аналізу для освітніх

платформ, описано архітектуру моделі та логіку її навчання на спеціалізованих корпусах текстів.

Розглянуто переваги та обмеження впровадження таких моделей у вищу освіту, а також потенціал інтеграції в системи LMS та сервіси підтримки зворотного зв'язку. Практична цінність дослідження полягає у формуванні інструментарію для швидкої, об'єктивної та масштабованої оцінки якості ВНС з метою вдосконалення навчального процесу.

***Ключові слова**: семантична нейронна мережа; аналіз якості; віртуальне навчальне середовище; освітня аналітика; глибинне навчання; обробка природної мови; когнітивні технології; дистанційне навчання.*

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