Using Ontologies and Knowledge Graphs to Individualize in E-Learning System

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Abstract
The article discusses the problems of individualization of learning (training) in intelligent learning systems based on ontological modeling and knowledge graphs. The concept of constructing individual learning trajectories in intelligent learning systems, which are then reflected in the corresponding knowledge graphs of the student and the knowledge graphs of the discipline, is considered. The proposed approach makes it possible to build formalized ontological models and flexibly configure an intelligent learning system to individualize the learning process for each student. An ontology for planning educational content has been developed in accordance with the individual learning trajectory, and the possibilities of its expansion in relevant online courses have been shown. A practical illustration of the application of the developed algorithm demonstrates provides a systematization of such problems and proposes approaches to solving them using knowledge graphs.

Keywords [1]
Intelligent learning system, ontological model, individualization of learning, individual learning trajectory, knowledge graph

1. Introduction

Within the framework of modern learning, there is a mixture of events of different characteristic directions - differentiated (based on differences) and undifferentiated (homogeneous in structure) events are divided between the main participants in the learning process – students and lectors (teachers). The tasks set for students are differentiated (for example, searching and analyzing information from various sources, checking the reliability of the information received, creating new knowledge based on their own assumptions, supported by knowledge from existing reliable sources, combining research methods, etc.). Therefore, the use of traditional tools and methods of knowledge management in teaching (such as lecturing, giving examples without in-depth analysis, conducting tests, etc.) related to undifferentiated events is not goal-oriented and the only source of knowledge transfer in the modern information environment.

Taking into the account the growing volume of information, interaction with students should be enriched by the use of differentiated tools and methods for transmitting, applying and creating knowledge. One of the approaches to increasing the effectiveness of training is the individualization of training, and in our time, most often e-learning. The problems of individualization of e-learning are outlined in [1, 2]. It should be noted that the interaction in e-learning and/or knowledge management in learning management systems occurs not between a person and a management system, but between the digital footprint, digital learning artifacts and an intelligent knowledge management system.

This feature gives rise to a number of new problems, in particular, such as:

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- searching for ways to present individualized training data;
- modeling of digital artifacts generated by e-learning systems;
- intellectualization of the analysis of educational data and/or knowledge;
- automation of the processes of adaptation and updating of educational content;
- individualization of learning processes (individualized provision of educational content and individualized route for advancement through educational content).

E-learning individualization processes are complex, affect the formation of individual competencies in students and relate to learning management systems (*LMS*) [3, 4], adding to them requirements for the formation of individualized content and ensuring the automatic selection of the most relevant (individualized) tools knowledge assessment.

Individualization refers to both individualized techniques [1] and individualized technologies [2]. This paper examines the second approach to understanding, since it is directly related to the processes of formation (including creation, modification and use) of e-learning educational content.

Individualization of learning in e-learning systems is important for further processes of digitalization of the economy and society, being the basis for the functioning and sustainable development of the corresponding digital ecosystem. Trends in industrial production towards the transition from mass production to personalized production, the intellectualization of all spheres of human activity, and the robotization of routine work are forming new professions that require the presence of specialists with unique sets of knowledge. The creation of individualized e-learning and knowledge management systems involves the use of special technologies (information, intellectual, training), knowledge bases, and the wider introduction of data mining methods and technologies.

The paper describes an approach to solving problems using knowledge graphs, ontologies and so-called "machine" learning technologies.

2. Building knowledge base in e-learning system

Nowadays, the basis for creating educational content in e-learning systems is the technology of MOOC (*Massive Open Online Courses*) [5], focused on mass learning. This creates a discrepancy between the needs of students and the capabilities (including the content of educational content) of e-learning systems.

Individualization of both e-learning systems and knowledge management systems in various subject areas (SA) can be achieved through the transition from databases and educational content repositories in LMS systems to full-fledged knowledge bases that provide appropriate knowledge representation models, logical inference methods and intelligent search. This requires an appropriate technological base for intellectualizing the tasks of managing both the formation and use of educational content, and the learning processes themselves. A modern approach to building knowledge bases is the use of semantic models and ontologies. For a formalized description of SA objects and processes, the Resource Description Framework (*RDF*) language is often used [6], which is a semantic graph model and is intended for representing semi-structured SA.

RDF specifies the architecture, syntax, semantics and basic dictionary of the RDF extension – *RDF* Schema (*RDFS*) [7] for constructing SA models. The main element of the *RDF* language is a triple of the form:

$$\langle subject, predicate, object\rangle, \qquad (1)$$

where subjects and objects can be unique (or named) entities to represent more complex structures (nested subgraphs, sets, etc.). Each entity has its own universal and unique resource identifier – *URI* (*Uniform Resource Identifier*) [8].

URI are used to refer to the entities being described. For example, the identifier of State University of Infrastructure and Technologies (*SUIT*, *DUIT* – in Ukranian) is *duit*, and *https://duit.edu.ua/* is the Internet address. Unnamed nodes – entities without an identifier (or literal) can contain other relationships and values. They are used in the modeling process to describe complex predicates and other constructs. Objects can be simple string literals representing subject attribute values. Predicates denote relationships between subjects or objects or properties (attributes) of subjects. Formally, triples (1) can be represented as elements

$$x_{ijk} = (e_i, r_k, e_j),$$

where $E = \{e_1, ..., e_{Ne}\}$ is the set of all entities (subjects or objects),

$R = \{r_1, ..., r_{Nr}\}$ – the set of all connections (relations) in the graph.

The set of triples forms an *RDF* graph, which can be defined formally [9].

Let V, B, A be disjoint infinite sets of *URI* $(V \cap B \cap L = \emptyset)$, unnamed vertices and literals, respectively. Then the *RDF* graph G can be defined as a directed multigraph:

$$G= (T, R, M, A),$$

where $T \subset (V \cup B \cup A)$ is a finite set of *RDF* terms corresponding to the nodes of the graph;
$R \subseteq T \times T$ – finite set of arcs connecting *RDF* terms;
$M \subset V$ – set of unique labels defined using *URI*;
$A: R \rightarrow 2^M$ – mapping arcs to a set of marks.

The *RDF* language is used to describe the basic elements of a knowledge graph, for example, “something is of this type” or “something is related to something,” but does not allow you to define classes of objects or configure sets of valid values for attributes.

RDFS introduces additional predicates, for example:

- *rdfs:Class* to define classes;
- *rdfs:Literal* to define literals;
- *rdfs:subClassOf* and *rdfs:subPropertyOf* to define relationships;

including hierarchical ones.

To build complex models of SA that use logical expressions as formal semantics, the *Web Ontology Language* (*OWL*) [10], which is an extension of the *RDFS* language, is used.

There are quite a lot of ontologies developed using *RDF*, *RDFS* and *OWL* that can be used to create customized e-learning systems, in particular the following:

- *Academic Institution Internal Structure Ontology* (*AIISO*) [11] – an ontology that describes the internal organizational structure of the educational process (based on classes and properties to describe courses, modules, practical and theoretical educational content).
- *Bibliographic Ontology* (*BIBO*) [12] – an ontology that describes bibliographic resources (descriptions of recommended literature, scientific publications, teaching aids and monographs).
- *Ontology for Media Resources* (*MA-ON*T) [13] – an ontology that describes media resources (based on the classes and properties of MA-ONT, lectures are associated with video materials).
- *TEACH* (*Teaching Core Vocabulary*) [14] – an ontology that describes educational content, is a dictionary with which teachers can connect objects of online courses.
- *FOAF* (*Friend of a Friend*) [15] – an ontology that defines some expressions used in statements about an object, for example: about the object “student” – this can be name, gender and other characteristics.

Among e-learning systems built on the basis of semantic technologies, we can highlight, for example, the following:

- *Metacademy* [16] – platform for open personalized education. The learning in the system is based on concepts of SA. In *Metacademy*, all educational material is educational content (courses, lectures, books are connected to each other using concepts of SA).

The user can create a course or roadmap based on the concepts they want to learn. Educational content is stored in appropriate ontologies, which allows users to navigate through theoretical material.

- *SlideWiki* [17] – platform for creating presentations for educational courses. Corresponding semantic technologies contribute, in particular:

– reuse already published presentation slides;
– annotate concepts on slides with additional information;
– support multiple languages for one training course.

To fully individualize learning, it is necessary, along with translating existing online courses into a semantic format (reflecting mainly the structure of the course and types of content, but not sufficient for building individual learning trajectories), to use a model of the student and his knowledge acquired in the process of studying the content. Without such a model, it is not possible to create an adequate individualization system.

The learner model promotes, in particular:

- generation of personalized recommendations for taking courses;
- organizing an adequate assessment of the knowledge acquired by the student;
- take into the account the individual needs of the student;
- formation of test and verification tasks corresponding to the individual learning trajectory.

As a rule, an online training course is organized linearly and consists of many modules and topics within modules. Semantic dependencies between modules are specified in the so-called course prerequisites (a description of all courses that should have been studied before studying the educational content of this online course). Depending on the specific choice of the student, you can build a chain of modules or courses that need to be studied.

Consider the following example. the student has chosen an introductory course in the Discrete Mathematics and in order to understand, for example, what the Turing Machine (or the Markov Normal Algorithm, or the recursive function) is, he must also study the concepts associated with the algorithm and its formalized description, which are introduced in the Theory of Algorithms course.

Such information can be found in the course prerequisites for the Discrete Mathematics. But including the entire course on the Theory of Algorithms or even a module on formalizing algorithms in an individual learning trajectory will be redundant for a given student.

It is enough just to limit yourself to the necessary components of educational content from the prerequisite courses, otherwise the student may end up with an overly overloaded trajectory.

To assess the student's knowledge, tests and assignments are selected from the appropriate database of assessment tools for assessing the student's knowledge. Each component corresponds to one of the terms T_i being studied. The transition points from course to course may not coincide with the boundaries of the modules. An individual learning trajectory is not static.

As you progress through the elements of the course, it can change, supplemented by new concepts, if necessary to understand the material and achieve learning goals. The process of constructing an individual learning trajectory is recursive in nature. For example, if in the considered example, when studying the topic "formalized description of algorithms," it is necessary to study the concept of "formalism," then the inclusion of this component in the individual learning trajectory can be done in a similar way to the inclusion of the topic "algorithm."

3. Building and using individual learning trajectories in e-learning system

Many *LMS* offer content management tools to build the individual learning trajectory, allowing you to create an individual sequence of courses for the student to study. At the same time, one should take into the account the fact that it is necessary to solve problems of accounting and analysis of data used to individualize e-learning.

Competency management in existing e-learning systems is based on mastering the educational content of courses without taking into the account the individual abilities and interests of the student (and often without feedback). In this sense, e-learning systems are linear, and learning itself is a monotonous process to achieve learning goals.

Building an individual learning trajectory in most cases involves the emergence of new points through which this trajectory will pass.

It is quite difficult to foresee in advance all possible points of an individual learning trajectory, which is due, in particular, to the following reasons:

- An individual learning trajectory is the result of the projection of several ontological models onto each other (course models, knowledge assessment models, cognitive model of the student, etc.). Forming a complete search space (for example, concepts, simple or complex elements of educational content) based on these models is often a computationally complex task with many contradictions, so its optimization requires the use of various heuristic methods and approaches.
- During the learning process, some of these models are changed, for example:
  - the student's cognitive model is replenished with new entities as he moves along the learning trajectory;
  - the student himself can make the adjustments, clarifying his needs;
  - it is possible for teachers to change course models; o updating educational content;

– models for the formation of individual learning trajectories can change as data accumulates and educational content changes.

- The learning process can be influenced by external factors (for example, market demands, economic, social and other factors related to education (learning, training).

Individualization of e-learning should be considered as a technology for creating intellectualization and management systems in education (learning, training), which should include, in particular:

– methods of ontological engineering;
– machine learning methods;
– semantic analysis and search tools;
– means of developing recommendations.

Modern *LMS*, in addition to the accumulated educational content, provide the necessary technological level for building individualized training systems on their basis, because databases are used to store data (including graph and *NoSQL* databases), presentation/display models of courses are not rigid and allow changes in their structure and composition, logging and subsequent analysis of user behavior in the system is carried out.

In the *LMS*, it is possible to connect services that integrate elements of new technology into the *LMS* and maintain continuity in the processes of learning and learning management.

To meet the described requirements for an e-learning individualization system, it is necessary to use the whole range of technologies to ensure interoperability and integration of the various components of such systems. An architecture that implements such the range of technologies should include, in particular, the following levels:

- Integration level:
  – data providers to the *LMS* database;
  – *API* to external data sources.
- Data management level:
  – metadata storage;
  – machine learning models for semantic analysis of *LMS* logs and creation or enrichment of ontologies;
  – templates for constructing semantic queries.
- Level of data analysis and intelligent services:
  – course ontologies that take into the account individualization;
  – cognitive ontological models of the student;
  – rules for generating of individual learning trajectory based on ontologies.
- Application and interface level:
  – recommendatory question-and-answer subsystems for interaction with students;
  – interactive visualization of technical equipment.

4. E-learning system: annotating educational content and learning outcomes

The educational content individualization subsystem, having gained access to e-learning data, must perform semantic annotation of this data (data from the database, semi-structured data (for example, system logs), unstructured data (text content or other text information (extended text responses of students to tests) , discussions, dialogues)).

Different types of data use different annotation methods. In all cases, as a result, it is necessary to obtain a certain set of objects that reflect the progress of the learning process (for example, completed course elements, achievements and competencies of the student) and the connections between these objects. Semantic annotations are some references to metadata that are expressed through ontology elements. When filling such an ontological model with instances of real data, a corresponding knowledge graph is formed.

To solve the problem of individualizing e-learning, the ontology must be a developed conceptual model, which includes layers of concepts of varying degrees of abstraction:

- high-level abstractions for modeling a student’s individual learning trajectory;
- general concepts of educational content and educational process;

- specific concepts for accessing and integrating e-learning system data in terms of SA.

The upper two levels do not depend on the specifics of the software and specific *LMS*, and the lower level, which can be divided into several sublevels if necessary, is adapted to specific requirements (for example, from students, teachers or the system).

When individualizing e-learning, modifications to the lower level of ontologies are performed because the individualization process involves building the separate model for each student based on the data that is used or generated during the learning process. Linking the abstractions of an individual trajectory and the structure of educational content is an operation on well-structured data that can be performed repeatedly for each student, ensuring a high level of objectivity of the results.

All this excludes any influence of the *LMS* administrator or expert on the result. Linking to the SA knowledge base level involves working with semi-structured and unstructured data and is performed once for each course. The accuracy of constructing supposed connections is higher with the participation of expert of the SA in this process. Modification of ontologies uses a set of machine learning methods and relates to Information Extraction tasks [18, 19]:

- Recognition/extraction of named entities (*Named Entity Recognition/Extraction*) – delimitation of positions of mentions of entities in the input text.

For example, in the sentence "What are the best programming languages for writing the kernel of an operating system?" underlined text is a reference to named entities.

- Linking/disambiguation of entities or semantic annotation (*Entity Linking/Disambiguation, Semantic Annotation*) – association of mentions of entities with a suitable and unambiguous identifier in the knowledge base.

For example, linking "Operating system" to the P306 entity, "Programming language" to the P277 entity in the knowledge base *wikidata* [20].

- *Term Extraction* – extraction of basic phrases that denote concepts relevant to the selected SA, including hierarchical relationships between concepts.

For example, identifying in a text about machine learning that "neural network" or "activation function" are important concepts in the domain under consideration, clarifying the concepts of "artificial intelligence".

- *Keyword/Keyphrase Extraction* – extraction of basic phrases that allow you to determine the subject category of the text (unlike extraction of terms, the task of extracting key phrases is to describe the text, not the subject).
- *Topic Modeling, Classification* – clustering of words/phrases that often occur together in a similar context. These clusters are associated with more abstract topics that the text is associated with.
- *Topic Labeling/Identification* – for clusters of words identified as abstract topics, extract a single term or phrase that characterizes these topics.

For example, defining that a topic consisting of {"machine learning", "sampling", "classification accuracy", "gradient descent"} is best characterized by the term "machine learning" (which can be associated, for example, with the concept Q2539 in *wikidata*).

- *Relation Extraction* – extracting potential n-ary relationships from unstructured or semi-structured sources.

For example, from the sentence "What programming languages are the best for writing the kernel of an operating system?" can be extracted are the best (programming languages, operating systems).

Binary relations can be interpreted as *RDF* triples after linking the relation predicates with corresponding properties in the knowledge base (such as discoverer or inventor (P61)).

5. Modeling in e-learning system based on knowledge graph

The individualized learning model is the knowledge graph of the disciplines being studied, supplemented by connections between concepts that are included in the student's set of acquired knowledge. Based on the totality of such connections for various students, one can judge the level of balance in the knowledge graph of the disciplines being studied, preferences and trends when students work with educational content. In addition, it is possible to harmonize and individualize (in the in the future study of this online-course) educational content and predict the most relevant options when building an individual learning trajectory).

The graph of a student's acquired knowledge is formed from a variety of concepts for describing the SA and is the subset of the general knowledge graph of all online-courses.

At the beginning of learning (training), this knowledge graph is empty. Then the starting set of concepts is placed in it, which is either determined by the result of the student's entrance (starting) test, or is obtained when studying the introductory course. In this knowledge graph, some concepts and connections are missing, which is due to the incomplete (partially incomplete, initially incomplete) volume of mastered knowledge in disciplines (courses). The knowledge graph of the particular student contains so-called "knowledge gaps," which are identified when compared with the general knowledge graph (of the given topic, the given course, the given discipline, or the given application).

To do this, the student's knowledge graph is projected onto the discipline's knowledge graph, which helps to restore missing nodes and add connections to the discipline's knowledge graph to determine the already completed part of the individual learning trajectory. Often, omissions of concepts in a student's knowledge graph are random, so solving the problem of finding a subgraph on the graph may contain quite a lot of errors. The vector representation of the knowledge graph is based on the distributional representation of the "hidden" properties of entities.

These properties for each entity (e_i) are specified by the vector $e_i \in R^{He}$, where He corresponds to the number of possible "hidden" properties in the model.

5.1. E-learning: students' knowledge graph

To restore missing nodes in students' knowledge graphs, an approach is used based on the joint use of vector representations of triplets from the knowledge graph and a text corpus based on educational content. This approach is effective, for example, when augmenting a knowledge graph based on the use of trained language models for a neural network [19]. Within the framework of the approach under consideration, nodes and connections of the knowledge graph are considered as text sequences consisting of labels and text descriptions of the corresponding triples.

After identifying missing concepts in students' knowledge graphs, it is necessary to determine the relationships between them in order to form a sequence for their study (including a list of courses, topics or modules that contain content that allows you to most fully study the selected list of concepts).

This is an important point in individualizing the presentation of educational content to the student, since the same concepts can be presented in different courses and in different volumes.

In addition, course content is updated periodically. These factors make any static projections of concepts onto concepts-structural elements (components, complex of concepts) of courses (topics, disciplines) ineffective. The use of a vector representation to restore connections in the knowledge graph contributes to the fact that in different courses, different contexts and a different set of connections can be used to link terms, and the connections themselves can have different domains of definition and domains of meaning, i.e. the same concept terms can have different sets of connections.

5.2. E-learning: evaluation of individual results

Tests and practical assignments are often not enough to obtain a reliable assessment of knowledge after completing an individual learning trajectory.

And generating tests for each such trajectory requires a large amount of resources and time for teachers when educational content is used by a large number of students.

At the same time, a significant amount of information about learning performance can be obtained by analyzing the student's digital footprint by examining logs and other digital artifacts that are generated while working in the e-learning system.

Something similar is used in software engineering when testing software.

When assessing student knowledge, digital artifacts can have the following types of data:

- logs of user behavior in the system (in particular, the number of visits to individual pages, time spent on each page, actions on the pages);

- user actions with educational content (for example, dynamics of video viewing, sequence of tasks, completion of started actions);
- activity when interacting with other users and the lector (teacher) through social services (number of questions, number of answers, regularity of sending messages, etc.);
- text data that is generated by the student when using a general chat or email;
- data from knowledge testing modules (closed and open tests, results of practical assignments, etc.).

The main methods for analyzing the data listed above include, in particular:

- extraction of named entities and relationships from text data;
- statistical analysis of logs [22];
- adapted unit testing methods [23].

6. E-learning system: ontological modeling

The formation and modification of an individualized learning trajectory in the e-learning system, when courses are studied not as a whole, but as separate components of educational content, can lead to a situation of chaotic mixing of the topics being studied, since the teacher's (lector's) plan, which was laid down when creating the online course, is ignored by the system [19. 21].

6.1. Ontological modeling of individualized e-learning

To eliminate this situation in the e-learning system, it is necessary to continuously monitor the semantic similarity of the studied set of topics and the content of the discipline (disciplines).

This is based on the use of approximation of the studied concepts by course ontologies, which allows the formation of an individualized learning trajectory to be focused on the subject of study by ranking the topics (modules, components, concepts) of the educational content of the course.

Semantic similarity assessment takes into the account three aspects that link the compared objects of the knowledge graph: hierarchy, proximity and specificity.

Hierarchical similarity analysis is based on identifying a set of hierarchical arcs on the knowledge graph G. Hierarchical arcs include those knowledge graph relationships whose property names belong to the hierarchical relationship, such as:

- *rdf:type*
- *rdfs:subClassOf.*

Semantic similarity assessment. uses hierarchical similarity methods and metrics for measuring hierarchical similarity between two objects when the nodes (vertices) of the compared entities in the graph have a common ancestor that is most distant from the root of the hierarchy tree and lies on both trajectories from these vertices to the root.

Calculation of the proximity of the neighbors of compared objects.

The environment of an object $e \in E$ is defined as the set of pairs:

<relationship>-<entity>,

where $N_e = \{(r, e_i) \mid (e, r, e_i) \in R\}$.

The entities of which are located at a distance of one step from e.

This definition of the environment allows consider together the neighbor entity and the graph arc relation type.

Semantic similarity assessment uses knowledge mapped in relationship and class hierarchies of knowledge graphs to compare two pairs.

The specificity of an entity e in the knowledge graph G is calculated as a value inversely proportional to the number of its incident arcs:

$Incident(e) = \{(e_i, z, e) \in R\}$.

Assessing semantic similarity involves calculating the specificity of the smallest common ancestor of e_1 and e_2.

The essence of this assessment is that entities whose common ancestor contains more general information are less similar than entities whose common ancestor contains more specific information.

6.2. Modeling of the cognitive student's profile

During the learning (training) process, a student's knowledge graph is formed, replenished with links to concepts of already studied SA [24].

The set of these links forms the cognitive profile of the learner. For each link in the learning process, a certain weight is calculated, characterizing the level of study of a particular topic.

The ontology of student contains the concepts and connections necessary for modeling [19]:

- what topics and concepts were studied;
- assessment of the quality of study (level of study);
- characteristics of the student himself, obtained by analyzing his actions in studying (learning, training) a particular topic (course, discipline, domain).

An important property of graph data is the possibility of various correlations arising between many interconnected nodes (in particular, vertices – components of educational content).

These correlations can be calculated, for example, using machine learning using attributes, relationships, and classes of related entities. Knowledge graph entities can be represented by vectors of their so-called "hidden" properties. These properties are called "hidden" because they are not directly described in the data, but can be inferred from the available data through a machine learning process. In particular, the following can be noted:

- additional tools for managing educational content and its presentation to the student are valuable for the learning process, showing the positive dynamics of the results of students studying a specific course in accordance with the individual learning trajectory;
- the effectiveness of using an individual learning trajectory is also determined by the fact that the e-learning system provides the learner with the opportunity to apply knowledge, such as "best practices", "lessons learned", where an analysis is carried out not only of the learner's successful and unsuccessful answers (or the results of his performance of the corresponding assignments).

But also includes annotation of typical errors, shortcomings and omissions (students are clearly presented with what actual errors may look like and are shown ways to find a solution to a specific problem). The ontological model of the course (discipline, SA) is formed for its joint use by teachers, experts in SA, stakeholders, etc.). The ontological model and knowledge graphs make it possible to separate knowledge about the SA (course, discipline) from the knowledge acquired by students.

The ontological model can be used when designing academic discipline programs that take into the account the possibility of using individualized learning trajectories for specific students and their needs and levels of prior knowledge (scientific, theoretical and practical basis), planning the structure of educational content, assessing the level of knowledge and competencies of the student and solving other problems.

7. Conclusion

Individualization in e-learning is a logical and necessary stage in the evolution of e-learning systems, which must move from mass production to personalization of learning processes.

This transition gives rise to many methodological, technological and conceptual problems. The ontological approach helps solve many of these problems. However, problems associated with the use of tacit or undeclared knowledge in e-learning systems cannot be solved only with the help of ontologies. The motivation for using individualized learning paths (as additional tools in learning (training, teaching)) may be the disadvantages of the traditional learning format:

- limited communicative dialogue between students;
- stereotypedness, monotony and lack of opportunities for critical thinking on the part of students;
- weak feedback.

The proposed approach, which involves performing, in particular:

- analysis of existing knowledge management tools in the learning process and presenting educational content to students;
- formation of an Individualized learning path and the corresponding knowledge graph of the student;

- adaptation and modification in the learning process of the Individualized learning trajectory and the corresponding graph of the student's knowledge.

The practical application of the proposed approach to e-learning based on the individualization of learning processes demonstrates its suitability for solving set learning tasks, increasing academic performance and engagement among students. The article provides a systematization of such problems and proposes approaches to solving them using knowledge graphs and their vector representations. The analysis can help in creating a new generation of e-learning systems, as well as in solving problems of processing and analyzing data from learning processes.

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