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DEVELOPMENT OF LEARNING CONTENT SELECTION AGENT BASED ON THE PROGRESS OF THE PARTICIPANT FOR TRAINING COURSES WITH GAMIFICATION

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Summary. *The work involved research, development and implementation of an educational content selection agent with gamification elements. Achieving the goal is due to the study of methods of selecting educational content based on the progress of the participant, as well as various approaches to the gamification of the process. According to the results of the study, the agent for selecting educational content is implemented. Approbation of the agent's work was carried out by introducing it into the developed learning environment.*

Key words: *training courses, recommendation, gamification, recruitment agent.*

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Formulation of the problem. Game-based learning is becoming increasingly popular in the modern world. However, well-designed game content can turn out to be a failure if it does not meet the needs of the learners. Therefore, a key factor in the success of such courses is the ability to effectively use data on the progress of participants and the relevance of the learning content to their needs. Depending on the type of recommendation object and the task to be performed by this system, it may have a different structure and complexity. Therefore, a simple system based on gamification will be developed to satisfy a large number of users.

Analysis of available research results. Based on the literature search on this topic, several articles directly related to the subject matter of the study were analysed.

In [1], the authors propose an architecture of a teaching environment with game elements for user training. One of its benefits is a thoroughly designed service architecture, which could help to develop their own. However, this paper is focused on cybersecurity education, so it may not be suitable for a wider user base. It also lacks a recommendation system.

The study [2] involves the development of a system for teachers that can help them use e-learning systems. It employs useful metrics to analyse each teacher's learning behaviour and approach, and is able to provide personalised feedback. Although these metrics are not suitable for the implementation of this work, it is possible to introduce our own metrics that will better reflect the essence of the system being developed.

In addition to developing a gamified system, in [3] the authors compare textual and visual representations of the game component of the work, which can be useful for deciding on the type of game. On the other hand, this paper does not provide many details of the implementation of textual or visual representation.

Another important component of implementing this work is making the best decisions for the user. An example of such experience is presented in [4], where solutions were made based on data from various sources, including user feedback.

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Objective of the research. Development and implementation of an agent for selecting educational content of training courses with gamification based on the progress of the participant in order to improve the effectiveness of educational courses.

Statement of the problem. To achieve the goal, it is necessary to solve a number of problems, namely:

To study and analyse the existing methods of selecting learning content based on the progress of the participant;

Develop an implementation of an agent for selecting learning content;

Implement and test the operation of the agent in real conditions on a specific course with gamification;

To assess the effectiveness of the agent for selecting training content in comparison with traditional teaching methods and other methods of selecting educational content;

Analyse the results and provide recommendations for further improvement of the agent.

Types of system recommendations. The system has the ability to recommend:

Materials based on a single question. Recommending materials based on a single question allows the personalised learning system to provide immediate, context-sensitive and relevant suggestions that meet the immediate needs or interests of the learner. For example, if a user answers a question incorrectly, the system can instantly offer them the best materials to deepen their knowledge of the topic. This helps to enhance their understanding, clear up any confusion, or expand their knowledge of that particular subject, meeting their learning needs more effectively. This targeted approach makes the learning experience more personalised and relevant, resulting in better engagement and better retention.

Recommending questions based on user progress. Question recommendation based on user progress is a key feature of the learning system, as it allows the system to adapt to the needs, abilities and performance of the student over time. This adaptive approach ensures that the questions presented to the user are well adapted to their current level of understanding, contributing to more effective and engaging learning. It also helps to structure the training process, allowing users to progress from basic concepts to more complex topics and gradually boost their knowledge. This progressive approach to learning can help build a strong foundation and reduce the chance of users being overwhelmed by more complex content.

Recommending materials based on the progress of the student. This recommendation provides a personalised learning experience that matches the current level of knowledge, interests and performance of the person. Delivering materials that are adapted to the progress of the user optimises the learning process, leading to a more engaging and effective learning experience. It also helps to create a flexible and adaptive course of study in which the content provided is matched to the current ability of a student. As learners progress and their understanding of the subject matter develops, the system can adjust recommendations accordingly, providing a continuous learning experience that supports the growth of knowledge and skills.

Attributes of the recommendation system. The main entities of the recommendation system are the progress of the participant and training materials. Progress consists of the answers to questions. The following difficulties have been identified in the agent implementation:

Data collection and storage. One of the main challenges in implementing such a system is collecting, organising and storing data on user activity. This includes properly tracking how users interact with the platform, recording their responses, and maintaining their progress through the learning materials.

Effectiveness and complexity of algorithms. Recommendation algorithms should be efficient and perform well under different conditions. As the number of users, questions, and materials in the system grows, algorithms must scale without compromising performance or recommendation quality. This requires careful optimisation and consideration of algorithm complexity.

Balancing the factors when making recommendations. To find the right balance between the various factors that will determine the correlation of questions to materials. The weights assigned to these factors in the scoring algorithm should be adjusted according to the desired results and user preferences. In addition, the scoring algorithm should take into account the recent interactions of the user and the history of questions to avoid repetition and maintain a high level of engagement in the learning experience. Therefore, these factors should be selected to be as informative and simple as possible.

Analysis of the main recommendation methods. One of the main attributes of the system is tags, and their comparison plays an important role in recommendation. Tags are a flexible and powerful tool that can significantly increase the efficiency, organisation and adaptability of a personalised learning system. By carefully selecting and assigning tags to questions and learning materials, you can create a dynamic learning environment that meets the needs of users and stimulates personalised content recommendations [5].

In particular, each question and material is assigned a list of tags that helps to identify its topic. Obviously, in this case, a measure needs to be introduced to determine how similar these lists are to each other. The main measure of similarity in this case will be the Jakarta index, a statistical measure used to quantify the similarity or coincidence between two sets.

The Jakarta index is calculated by dividing the intersection of the two sets (i.e., the number of items common to both sets) by their union (i.e., the total number of different items in both sets combined).

Mathematically, the Jaccard index (J) of sets A and B is calculated by formula 1:

$$J(A,B)=(|A\cap B|)/(|A\cup B|), \tag{1}$$

where $|A\cap B|$ represents the size of the intersection of sets A and B, and $|A\cup B|$ represents the size of the merge of the two sets.

The resulting index is in the range from 0 to 1:

1. A Jaccard index of 0 indicates that the two sets have no elements in common.
2. A Jaccard index of 1 indicates that the two sets are identical and have all the same elements.

In this system, a higher Jaccard index means a higher degree of similarity between tags, which can inform recommendation algorithms to present related content to users based on their interests or learning needs. For example, if two learning materials have very similar tags, they are likely to have a similar subject matter, making them recommendation options.

Another basic entity for recommendations is user progress. Due to the simplicity of the attributes (tags and difficulty), user progress is also a very simple but effective element.

User progress consists of two parts: tag progress and difficulty progress. These components have the same structure. For example, tag progress is a set of key-value pairs, where the key is a specific tag and the value is a structure with the following properties:

1. The number of questions with a key tag answered correctly by the user;
2. The number of questions with the key tag answered incorrectly by the user;
3. The date of the latest interaction between the user and the question with this key tag.

Difficulty progress has the same structure, where the key is not a tag but a level of difficulty.

Recommending questions based on the progress of the user. The progress of a user consists of the statistics of their answers to questions. The system collects statistics from each answer, regardless of the correctness of the answer, and can make certain recommendations based on these statistics. In particular, it can recommend other questions.

1. Detecting question duplication: determines whether a question has been answered recently or during the current quiz. This information is later used to penalise scores if the question has already been asked, contributing to the diversity of recommendations.

2. Calculate a tag-based score: For each tag associated with a question, it analyses how users perform in that particular tag or topic based on their interaction history. Higher scores are assigned to questions with tags related to areas where the user needs improvement or shows interest.

3. Difficulty-based score adjustment: takes into account how well a user performs on questions of a certain difficulty and adjusts the question score accordingly. This ensures that the recommendations are appropriate to the skills level of the learner and provide an optimal level of difficulty.

4. Duplicate penalty is applied: reducing the score of questions that have been answered recently or during the current quiz. This step provides a variety of recommendations, preventing users from asking the same questions repeatedly and keeping them engaged in the learning process.

5. Determine the final score and ranking of questions: combines the calculated tag-based score, difficulty adjustments, and repetition penalties to give a final score for each question.

When recommending questions based on user progress for each question, the following key steps are taken to ensure that the recommended questions are relevant to the needs and preferences of the learner:

Following these basic steps, the system calculates and assigns points to questions based on the progress, performance, and interaction of the learner. This approach generates adaptive, targeted, and engaging question recommendations that meet the unique needs and preferences of each user, ensuring effective learning.

Gamification elements. The use of gamification elements can bring significant benefits to the users of systems. The inclusion of game mechanics can improve the learning experience by promoting motivation, engagement and effective learning [6]. Three elements of gamification are implemented in the system.

The first element – quiz helpers (50/50, «Try again») – earning coins for correct answers, the user may spend them when answering other questions.

The second element – a system of levels – for correct answers to questions, the user gains experience that is converted into a user level.

The third element – achievements – in the process of learning, the user will receive achievements for certain ‘milestones’.

Thus, incorporating gamification elements can significantly improve a learning system by promoting user engagement, motivation, and overall learning effectiveness. By rewarding and supporting users throughout their learning journey, these game-based mechanisms create a more enjoyable, interactive and productive learning environment [7].

Research results. To solve the problem and test the results, the following technology stack was used:

JavaScript is a versatile and widely used programming language that is mainly employed to add interactivity and dynamic content to websites.

React is a popular open-source JavaScript library for developing user interfaces and web applications. It is popular primarily due to its performance advantages, reusable components, and a large and active community that develops and maintains a wide range of additional tools, libraries, and frameworks.

Next.js is a popular open-source platform built on top of React that simplifies the development, optimisation, and deployment of web applications. Next.js supports different rendering strategies out of the box, such as static site generation, server-side rendering, and client-side rendering, allowing developers to choose the best approach for each page in their application depending on the requirements. This will simplify the implementation of our system, as it will frequently call the API, which, by the way, can also be easily implemented in Next.js.

PostgreSQL is a powerful open-source relational database management system (RDBMS) that emphasises extensibility, stability, and adherence to SQL standards. It has an active community of developers, contributors, and third-party tools, libraries, and extensions that ensures the continuous growth and development of the platform.

Since the system operates only with tags and difficulty levels that describe questions and materials, they can be generated randomly for simplicity of implementation and this will not affect the recommendation ability of the system.

Materials will be generated as follows:

1. Each material is assigned a unique identifier
2. Each material is assigned a name with a random number in the format Material <number>.
3. URL: https://example.com/
4. The tag list is filled with a random number of unique tags. The system currently contains tags Tag 0 – Tag 9 (10 tags in total).
5. Select a random level of severity. There are 4 difficulty levels in total – Novice, Intermediate, Advanced, Expert.

For questions, the generation process is the same, except for the following:

1. The name of the question has the format Question <number>.
2. The answer options for all questions are Answer 1 – Answer 4 (4 options in total)
3. The correct answer is selected randomly.

Fig. 1. and Fig. 2. show the generated materials and questions, respectively.

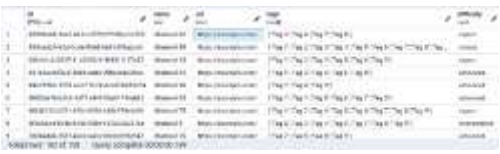

Figure 1. Generated materials

Figure 2. Generated questions

For testing purposes, a simple learning environment with all the necessary functionality for a recommender system was created. The home page is a navigation page for all the main actions of the environment and is shown in Fig. 3.

Figure 3. Home page of the system

View questions is a link that takes the user to the page with all the questions (useful, for example, for administrators) (Fig. 4.) It is also possible to add new questions (Fig. 5.).

Figure 4. Page with whole list of questions in the system

Figure 5. Page for adding new question

Similar functionality is available for viewing materials in the system (Fig. 6 – Fig. 7).

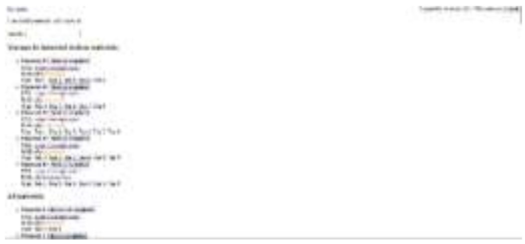

Figure 6. Page with whole list of materials in the system

Figure 7. Page for adding new material

Figure 6 also shows one of the recommendations based on the progress of the user. For the current user, the system recommends 4 materials of the advanced level and 1 material of the intermediate level. It can also be seen that among the tags, the system recommends mainly tags 5 and 8, which indicates that the user most likely has knowledge gaps in these tags.

The main source of data for the system is the responses of the user to the questions. For this purpose, the environment has a quiz available at the *Try quiz* link. Each question in the quiz is recommended based on the participant's past performance, including in the current quiz. The first question recommended by the system is immediately visible on the screen (Fig. 8).

The system recommends expert-level questions since the user is confident enough to answer questions at this level. The progress of the user through the levels is shown in Fig. 9.

Figure 8. Page with recommended question

Figure 9. Progress of the user by level

These materials will most often be of the same level of difficulty, or not very different. The following questions may be of a different level, depending on the correctness of the answers. If the user answers a question incorrectly, the system recommends materials that can help them learn (Fig. 10). These materials will often be of the same complexity level or not much different.

Figure 10. Recommendation of the materials based on question

Fig. 11. and Fig. 12. show several questions that the quiz will recommend if you answer them correctly.

Figure 11. Question 1

Figure 12. Question 2

The system recommends expert-level questions. If a question is answered incorrectly, its level may be lowered over time. It should be noted that the complexity is not the only factor that influences the recommendation of a question. Another important aspect is tags, and since the system in this implementation tries to fill in the gaps in the knowledge of the learner, questions with tags that are often answered incorrectly by the user can be recommended to him regardless of the difficulty level.

Gamification elements have also been introduced into the learning environment. One of these elements is shown in Fig. 13.

Figure 13. Additional features during passig the quiz

Users earn currency for each question: 50 for questions of the novice level, 100 for intermediate, 200 for advanced, and 300 for expert.

There are 2 purchases available to help users.

50/50 – reduces the number of possible answers by half. The cost is 200 currency. An example of work is shown in Fig. 14. Another purchase – «Try again» – allows the user to answer the question again if the first answer was incorrect.

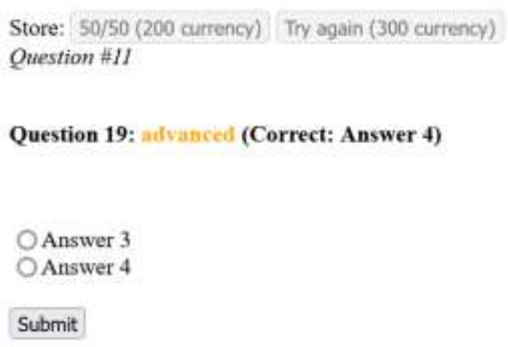

Figure 14. Example of work 50/50

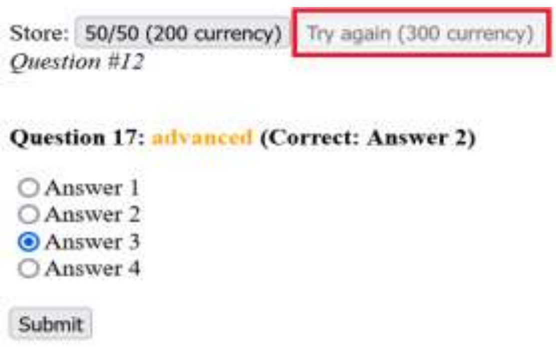

Figure 15. Option «Try again» is blocked, as there was no answer on the question yet

There is also a system of achievements that will encourage the user to improve their knowledge (Fig. 16). This page is available at *See your achievements*.

Figure 16. Page of user's achievements

Achievements marked in green are completed. The conditions and progress of the achievement can be seen below each of them.

Conclusions. In this paper, the existing recommendation algorithms have been analysed, their advantages and disadvantages have been estimated. The principle of operation of the developed system, its attributes and algorithms were also described. The developed system has been implemented in a customised learning environment.

When analysing the sources and existing systems, it was determined that they were highly specialised and did not correspond to the subject of the work, so this work will be new.

When analysing methods and algorithms for recommendation, two main attributes were taken into account, based on which a recommendation will be made: tags and complexity. Tags describe the content of the resource, and complexity describes the level of knowledge required by the user. These are two simple, yet extremely informative attributes that, when combined, can describe the content of the entity being covered in a very concise and effective way.

The recommendation system is implemented on the basis of similarity and fines – the algorithm compares two entities and determines how similar they are, and then also includes fines under certain conditions. This creates a list of evaluated items, where a higher score means a more suitable item for recommendation. There is also a training environment in which the recommendation system is implemented to test the system in real-world conditions.

Gamification elements have been added to the learning environment to help users better develop their knowledge and skills through greater engagement and motivation.

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РОЗРОБЛЕННЯ АГЕНТА ПІДБОРУ НАВЧАЛЬНОГО КОНТЕНТУ НА ОСНОВІ ПРОГРЕСУ УЧАСНИКА ДЛЯ НАВЧАЛЬНИХ КУРСІВ З ГЕЙМИФІКАЦІЄЮ

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Резюме. *В сучасному світі зростає популярність навчання з використанням геймифікації. Однак добре спроектований ігровий контент може стати невдалим, якщо він не відповідає потребам учасників навчання. Відтак, ключовим фактором успіху таких курсів є здатність до ефективного використання даних про прогрес учасників та відповідність навчального контенту їхнім потребам. Одним із основних завдань роботи є розроблення агента підбору навчального контенту на основі прогресу учасника для навчальних курсів з геймифікацією. Для досягнення цієї мети використано різні методи, такі, як збір та аналіз даних про прогрес учасників, проектування ігрового контенту, а також машинне навчання для підвищення точності рекомендацій. Обґрунтування вибору цієї теми полягає в тому, що ефективний агент підбору навчального контенту може допомогти підвищити мотивацію та результативність учасників навчання, що, в свою чергу, може призвести до більшої успішності курсу в цілому.*

Мета роботи полягає в розробленні та впровадженні агента підбору навчального контенту на основі прогресу учасника для навчальних курсів з геймифікацією для підвищення результативності навчальних курсів.

Об'єкт дослідження – процес підбору на навчальні курси на основі прогресу учасника з використанням геймифікації.

Предмет дослідження – ефективність і точність роботи агента, а також його вплив на результативність учасників курсу.

Методами дослідження є рекомендаційні алгоритми на основі подібності.

Новизною дослідження є навчальне середовище з упровадженою рекомендаційною системою та елементами геймифікації.

Практична цінність полягає у тому, що зі зростанням популярності віддаленого та самостійного навчання, зростає необхідність у якісних навчальних середовищах, що допоможуть користувачам самостійно вивчати необхідний і актуальний для них матеріал.

Ключові слова: *навчальні курси, рекомендаційна система, геймифікація, агент підбору.*

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