Microservice Architecture of the Learning Personalization System Based on the Analysis of Students' Behavioral Data

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Abstract

The article discusses the importance of personalized education in the modern world, where each student has different abilities, knowledge, and interests. Personalization of education allows adapting educational trajectories to meet the individual needs of students, which helps to increase motivation and academic performance. The literature review covers modern approaches to analyzing student behavioral data, the use of artificial intelligence, big data, and adaptive learning. The article proposes an innovative model for personalizing the learning process based on behavioral data using microservice architecture and intelligent agents. The model includes systems for collecting and analyzing data, adapting learning materials, monitoring progress, and integrating privacy mechanisms.

Keywords

distributed computing, microservice architecture, intelligent agents, cloud computing, personalization of learning 1

1. An Introduction to methods of processing students' behavioral data

In today's world, personalized education is becoming increasingly relevant as it allows for a more efficient, individualized and modern learning environment that meets the requirements of the present and the future. Since each student has different abilities, level of knowledge, learning style, interests and motivation, personalized education allows you to adapt the learning process to individual needs, which increases its effectiveness and makes learning more comfortable for everyone. In the modern world, the amount of knowledge is constantly growing, and the same approaches for all students are becoming less effective. Personalization helps to better structure the learning process by selecting exactly the materials and methods that are most suitable for a particular student. The use of artificial intelligence technologies, big data, and adaptive learning systems allows to effectively analyze data on students' learning progress and automatically adapt educational trajectories. This makes personalized education not only possible but also scalable. Students who receive learning materials and assignments according to their interests and level of knowledge are more motivated and interested in learning. This contributes to deeper learning and improved academic performance. The modern labor market requires individual skills and competencies. Personalized education prepares students to solve real-world problems by developing the skills they need to succeed in their professional lives.

Analyzing student behavioral data is a key element in achieving personalized education, as it allows you to:

- Identify individual needs and difficulties. Data analysis allows you to identify the problems that students face and reveal their strengths and weaknesses. This makes it possible to adapt

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the learning process to a particular student, helping them overcome difficulties and learn the material more effectively.

- Predict academic performance. With behavioral data, you can predict whether a student will have problems in the future and intervene in time. This allows you to avoid potential difficulties by adjusting the learning trajectory in advance.
- Optimize learning resources. Personalized learning involves providing each student with individualized recommendations for materials and tasks. Data analysis helps to determine which resources are most suitable for each student, which increases learning efficiency.
- Increase student motivation. When learning materials and assignments are tailored to a student's skill level and interests, it helps to increase engagement and motivation.
- Adapt the pace of learning. By analyzing data on student activity, you can adjust the pace of learning by increasing or decreasing the number of new topics according to the student's capabilities, which helps to avoid overload.

In general, behavioral data analysis allows you to create individualized educational trajectories that take into account the unique characteristics of each student, contributing to their successful learning.

2. Related Works

The purpose of the literature review is to investigate existing approaches to behavioral data analysis, to identify the main methods and technologies used in the educational process to personalize education.

In early studies, methods such as surveys, testing, or observation were used to analyze student behavior.

The study [1] examines the relationship between two indicators of learning effectiveness - student surveys and classroom observation - to determine whether their correlation depends on the study design. The dependencies are investigated using generalization theory. The results indicate that the correlation between surveys and observations depends on the number of classroom observations, the number of student assessments, and whether projects are nested or partially nested.

The study [2] focuses on the year-to-year stability of student observation and survey measurements, based on data from the Measures of Effective Teaching (MET) study conducted by the Bill & Melinda Gates Foundation. The results indicate that the methods of observation and student surveys used in MET are somewhat more stable than measures of faculty contribution to student learning, but the stability is lower than that of comparable measures in higher education. Nevertheless, reclassification rates based on these indicators are high, especially if they are based on estimates of reductions in criteria.

One of the problems associated with the study of student engagement is the large variations in measurement tools, which makes it difficult to compare the results of different studies. Paper [3] examines the measurement of student engagement in three ways. First, the authors describe the strengths and limitations of different methods of measuring student engagement (i.e., self-report measures, experience sampling methods, teacher ratings, interviews, and observations). Second, they compare 11 indicators of student self-reported engagement that have been used in previous research. In these 11 measures, the authors describe what is measured (scale name and items), the use of the measure, samples, and the degree of reliability and validity of the information available for each measure.

The amount of information is constantly increasing as students use learning management systems and digital learning environments during their studies. This greatly expands the possibilities for better understanding how students learn. The learning analytics community studies this data to describe learning processes and make recommendations for improving the learning environment.

Modern approaches allow for a more detailed analysis of student behavior based on big data analysis, artificial intelligence (AI), machine learning, and other technologies.

One of the challenges is the need for more and more detailed information about each student's learning processes in order to develop useful and timely feedback for students and teachers. Various studies have consistently demonstrated a positive relationship between engagement and academic success. However, in order to build learning analytics that describe student engagement and recommend more productive forms of engagement, it is necessary to better understand what student engagement means, how it can be observed online and quantified, and how it relates to learning processes and achievement [4].

Currently, there is no standardized, holistic approach to data storage and collection in educational institutions, which results in very large, incomplete, and heterogeneous student data sets. The authors of [5] investigate student engagement patterns using various data visualization and statistical analysis techniques to develop an understanding of student engagement with course resources over the course of a semester.

Learning Analytics focuses on collecting and analyzing learner data to improve their learning experience by providing informed instruction and optimizing learning materials. To support research in this area, the authors of [6] developed a dataset containing data from courses offered at the Open University (OU). This dataset is unique in that it contains demographic data along with aggregate data on student interaction in the virtual learning environment (VLE). This allows us to analyze student behavior as represented by their actions.

Higher education researchers have developed measures to assess student engagement in higher education and have investigated the experiences that promote student engagement and whether student engagement leads to important college outcomes such as college persistence, academic achievement, cognitive development, and other affective outcomes. The researchers in [7] conceptualized and measured student engagement, and discussed research on student engagement in higher education, focusing on four sets of factors: antecedents of student engagement, facilitators of student engagement, indicators of student engagement, and outcomes of student engagement.

The authors of [8] reviewed 140 studies and were unable to find any specific survey that focused only on classroom learning. They focused on identifying predictors, methods used to identify, time and purpose of predicting student performance.

According to a review [9], several machine learning (ML) methodologies are used to identify and solve the fundamental problems of predicting at-risk student performance and student withdrawal rates. In addition, most studies use data from college/university student databases and online learning portals. ML methods have been found to play a crucial role in predicting student risk and withdrawal rates, and thus, in improving student performance.

The need for assessment of student learning is becoming increasingly necessary to optimize integrity and help students achieve superior learning outcomes. One of the critical challenges is the lack of an accurate and effective assessment method. Predictive analytics (PA) can help organizations make more intuitive and intelligent decisions. Previously, scholars have presented several strategies to develop an optimal process framework using various academic statistics, methodologies, techniques, and platforms. Numerous learning problems, such as categorization, prediction, and cluster analysis, are related to the predictive analysis used in student achievement assessment. The student performance prediction model has various advantages and applications, for example, it is used to help teachers in developing and improving the curriculum. Student performance prediction (SPP) provides recommendations to students and offers comments to teachers. In [10], several student performance prediction (SPP) methods are compared using performance parameters such as accuracy, specificity, and sensitivity.

In particular, data mining has been used to predict a variety of important educational outcomes, such as performance [11], retention [12], success [13, 14], satisfaction [15], achievement [16], and dropout rate [17].

The study [18] provides a step-by-step set of guidelines for educators who want to apply data mining techniques to predict student performance. a wide range of factors that can potentially influence the prediction of student academic performance. The definition of what academic performance is, as well as the potential influential factors that affect the prediction of student academic performance (the number of papers that investigated this particular factor is indicated in %):

- Previous academic achievements (44%). Pre-university data: secondary education (i.e., high school results), pre-entry data (e.g., entrance exam results). University data: semester GPA or CGPA, individual course letter grades, and individual grades.
- Student demographics (25%), Gender, age, race/ethnicity, socioeconomic status (i.e. parents' education and occupation, place of residence/distance traveled, family size, and family income).
- E-learning activity (17%), Number of logins, number of assignments, number of tests, grades, number of posts on the discussion board, number/total time spent viewing the material.
- Psychological characteristics (11%). Student interest, learning behavior, stress, anxiety, time spent being busy, self-regulation, and motivation.
- Student environment (3%). Class type, semester length, program type.

The methodology for conducting a survey among students and teachers, where intelligent agents analyze their responses and generate recommendations for improving the educational process, is given in [19].

The approach that combines agent technology and computer vision allows for the provision of online educational services, enables students to stay informed about the progress of their own learning activities, and allows both teachers and parents to monitor student performance [20].

The analysis allows us to draw several key conclusions:

- Data collection is evolving. From early methods such as surveys and observation, modern research has moved to the use of big data and artificial intelligence to personalize education. This expands opportunities for more detailed analysis of learning processes and timely feedback.
- The importance of student engagement is increasing. Student engagement has shown a positive correlation with academic achievement. For effective monitoring of engagement, it is necessary to improve observation methods and their quantification, in particular in online learning environments.
- There is a need for data standardization. Many studies lack standardized approaches to data collection, which makes it difficult to compare results and implement common solutions for educational institutions. This leads to heterogeneity and incompleteness of training data.
- The use of machine learning and data mining plays a key role in predicting student performance and the risk of dropping out. Predictive analytics helps organizations and educators make informed decisions to improve learning processes.
- The main factors that influence student performance include previous academic achievement, demographics, e-learning activity, psychological characteristics, and the learning environment. Taking them into account is critical for building effective forecasting models.

These findings emphasize the importance of further research in the area of student behavioral data analysis, especially in terms of standardizing data collection and analysis methods, as well as the introduction of modern technologies to improve learning outcomes.

The purpose of this study is to develop an innovative model of personalization of learning based on the analysis of student behavioral data, which will allow individualizing learning processes, increasing learning efficiency and providing personalized support to students. This is achieved through the use of a flexible and scalable microservice and intelligent agents that automate progress monitoring, adaptation of learning materials, pace and learning styles in real time.

3. Methodology for building a model of learning personalization based on the analysis of student behavioral data

We propose the following practical steps necessary to achieve individualized learning based on the analysis of student behavioral data:

Step 1. Development of a system for collecting, analyzing and processing student behavioral data.

Step 2. Implementation of Learning Analytics to identify patterns in learning activities and predict academic performance.

Step 3. Development and implementation of an algorithm for personalizing learning paths.

Step 4. Development of an adaptive learning model that automatically adjusts the pace and content of learning materials according to students' needs.

Step 5. Providing effective feedback between students and teachers through a monitoring and analytics system.

Step 6. Integration of intelligent agents to automate decision-making processes and personalize the educational experience.

Step 7. Development of a privacy policy and protection of students' personal data within the educational platform.

To combine these tasks in a single model, it is necessary to develop a comprehensive, multi-component system that integrates various technologies, methods and approaches to adapt the educational environment and individualize learning. The proposed model consists of several interconnected blocks, as shown in Figure 1.

In the proposed system, the components interact as part of a single cycle where data is collected, analyzed, adapted to the needs of students, and the results are used to continuously improve the learning process.

Data Collection and Processing Module is responsible for receiving all data from students, teachers, learning platforms, and other agents. It interacts with intelligent agents to collect a variety of data (activities, test results, feedback, etc.). Once collected, the data is transferred to the Learning Analytics Engine for further analysis.

Learning Analytics Engine analyzes the collected data using Evaluation Algorithms to determine the success of the training, possible problems or ways to improve. This block is closely related to the Adaptive Learning Module of the learning process, as the results of the analysis are used to adjust learning trajectories.

Adaptive Learning Module uses data from *the Learning Analytics Engine* to dynamically adapt the course or content of learning materials to the individual needs of students. It works in conjunction with Intelligent agents to provide personalized recommendations and learning experiences.

Intelligent agents use data from the *Data Collection* and *Processing Module* and works with the *Adaptive Learning Module* to generate personalized recommendations for each student. Intelligent agents monitor progress, communicate with students and teachers, and support *Feedback and Communication Module.*

Feedback and Communication Module provides regular feedback between students and teachers based on data collected by agents and analyzed by the *Learning Analytics Engine*. It interacts with Intelligent agents to promptly report changes or problems in the learning process.

Security and Privacy Module is responsible for maintaining the confidentiality and protection of data transmitted between all components of the system. It interacts with all components, especially the *Data Collection* and *Processing Module*, to ensure that data is collected, transmitted, and stored securely.

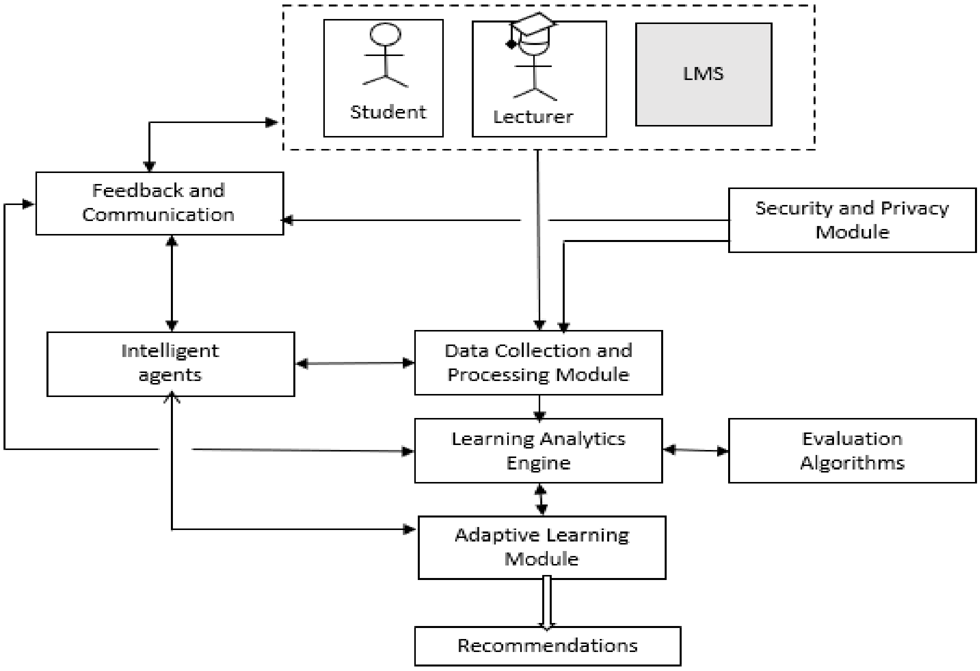

Figure 1: A model of learning personalization based on the analysis of student behavioral data.

Evaluation Algorithms are used to process data in the *Learning Analytics Engine*, determine learning outcomes, and evaluate the effectiveness of the learning process. These algorithms influence the work of the *Adaptive Learning Module*, forming learning paths and recommendations for students.

Thus, these components are integrated into a single model to create an individualized learning environment.

3.1. Microservice architecture of the learning personalization system

To ensure scalability, flexibility, and ease of maintenance, we will implement a model for adapting the educational environment based on the analysis of student behavioral data using a microservice architecture.

All microservices and their interaction to fulfill a user request to analyze student behavioral data to provide recommendations are shown in Figure 2. This request is divided into smaller tasks, each of which is processed by a separate microservice:

1. *Data Collection and Processing Service* uses APIs to integrate with learning platforms and external sources.
2. *Learning Analytics Service* Saves analysis results in the database.
3. *Adaptive Learning Service* generates personalized recommendations for students.
4. *Intelligent Agents Service* responsible for progress monitoring and communication.
5. *Security and Privacy Service* controls data security and ensures compliance with privacy standards and uses encryption to transfer data between services.

In Figure 2, arrows indicate calls between different parts of the system, and the numbers next to the arrows show the sequence of calls:

- «1»– Request: analysis of student data;
- «2» – Add student ID, date range;

- «3» – Asynchronous reading of the event monitoring of student behavior;
- «4» – JSON representation student's data;
- «5» – Analyze data;
- «6» – JSON representation of analysis results;
- «7» - Get analytical data;
- «8» – JSON representation of recommendations;
- «G (ϕ_1)» – Check access for all incoming requests;
- «G (ϕ_2)» – JSON representation information about the state of security in the system;
- «9 «– Response: recommendations.

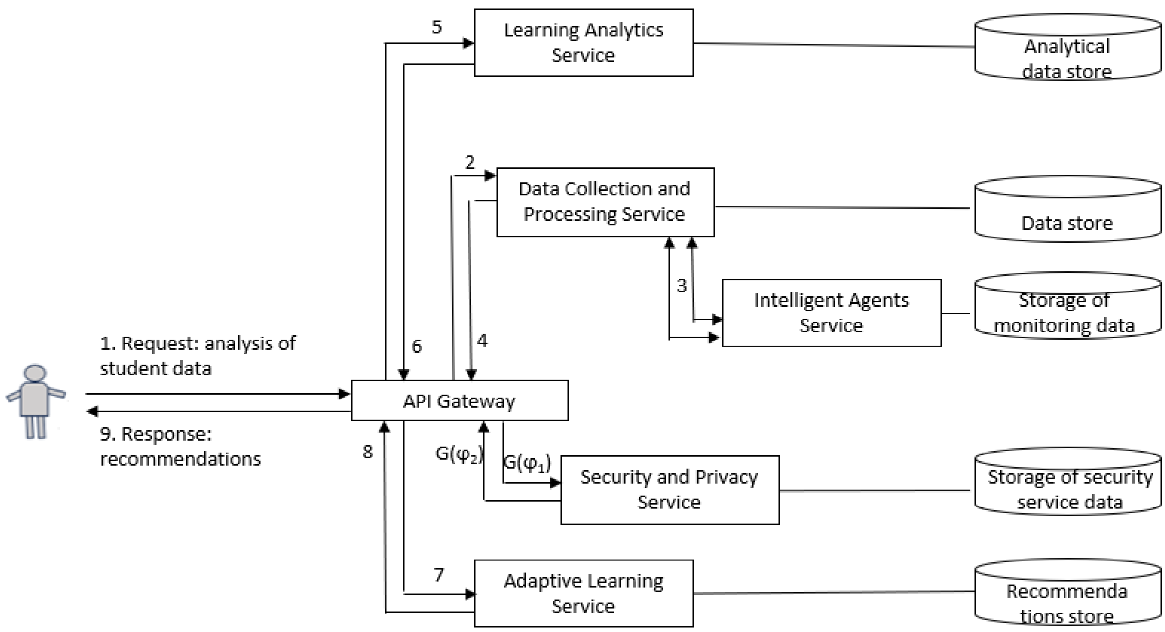

Figure 2: Microservice architecture of the learning personalization system based on the analysis of students' behavioral data.

Modal operator G (ϕ_i) means «**G**lobally»: ϕ_i *must be true in all future states.* Thus, in order for the Security and Privacy Service to constantly perform its functions, it will use access control. The API Gateway performs access checks for all incoming requests. “The Security and Privacy Service provides authentication and authorization mechanisms that will be used by the API Gateway.

Interaction between microservices is realized through the API Gateway based on the C#/Nancy/OWIN technology stack, which is used to route requests to the appropriate microservices and provides a single interface for external clients. Nancy is used to create HTTP APIs, and OWIN is used for hosting. REST API is used for synchronous communication between microservices. Each microservice has its own database (PostgreSQL for Learning Analytics, MongoDB for Data Collection) to store specific data. The Prometheus monitoring system and the ELK Stack logging system are used to track the operation of microservices. API Gateway is needed to coordinate requests between different microservices. It accepts requests from clients and transmits them to the appropriate services.

3.1.1. Microservice Learning Analytics Service

To test the proposed microservice architecture, we use a simple logic for analyzing student behavioral data, which is designed to evaluate student academic activity and performance based on the collected data.

The input data are:

1. information about the student's interaction with the learning platform:

- login frequency (*LoginFrequency*);
- number of completed tasks (*TasksCompleted*);
- total number of tasks (*TotalTasks*);
- total time spent studying (*TotalTimeSpent*));

2. information on the quality of student interaction with the material and teachers:

- positive feedback (*PositiveFeedback*);
- negative feedback (*NegativeFeedback*);

3. information about the student's academic achievements:

- average score (*AverageGrade*);
- number of completed modules (*CompletedModules*).

All data on student activity and performance is collected by intelligent agents from various sources (APIs of learning platforms, databases, etc.). The collected data is combined into a single structure for further analysis.

Student activity is determined based on the following indicators:

- If the student's login frequency is less than 3 times per week, the student is defined as "*Low Activity* ".
- If the number of completed tasks is less than 50% of the total, the activity is considered "*Moderate Activity* ".
- If a student has completed more than 50% of the assignments, he or she is classified as "*High Activity* ".

Let's formalize the rules as follows:

- if *LoginFrequency* < 3, activity = "*Low Activity*";
- if *TasksCompleted* / *TotalTasks* < 0.5, activity = "*Moderate Activity*";
- if *TasksCompleted* / *TotalTasks* >= 0.5, activity = "*HighActivity*".

Risk is assessed based on a combination of student performance and activity:

- If the student's average grade point average is less than 60% and the login frequency is less than 2 times per week, the risk is defined as "*High*".
- If the average score is more than 60%, but the login frequency is less than 2 times per week, the risk is defined as "*Moderate*".
- If the student's login frequency and grades are within the normal range, the risk is "*Low*".

To determine the risk, the rules are as follows:

- if *AverageGrade* < 60 and *LoginFrequency* < 2, risk = "*HighRisk*";
- if *AverageGrade* >= 60 and *LoginFrequency* < 2, risk = "*ModerateRisk*";
- else, risk = "*LowRisk*".

Initial data:

- Assessment of student activity: Classification of students based on their activity ("*Inactive*", "*Moderately* active", "*Active*").

- Risk assessment: Determine the risk level of the student (*"High risk", "Moderate risk", "Low risk").*

The main routes for Learning Analytics Service include:

- Collecting data on student learning.
- Processing and analysis of behavioral data.
- Saving the results of the analysis in the database.

The results of analyzing student behavioral data are stored in the Analytical data store. The connection to the database is made through the Entity Framework.

This logic allows you to add new rules for different scenarios, which helps the system take into account more factors:

- Determine not only the frequency of assignments but also the pace of progress.
- Take into account the type of assignments (e.g., practical or theoretical), the complexity of the modules, or the importance of the disciplines.
- Expand the number of activity classifications: for example, "High activity, but low quality of assignments".

This basic logic allows you to collect student behavioral data, perform analysis, and generate personalized recommendations. This formal description can be used as a basis for further implementation of more complex algorithms or integration with machine learning tools to improve the accuracy of the analysis.

Microservice *Learning Analytics Service* consists of the following components (Figure 3):

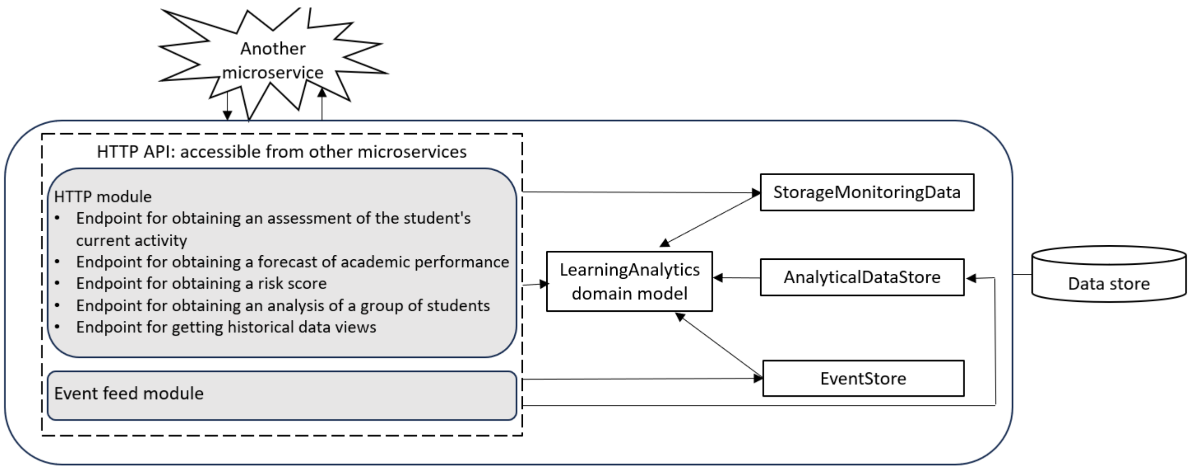

Figure 3: Microservice model *Learning Analytics Service.*

- An analytical domain model that is responsible for implementing any rules related to data analysis.
- The HTTP API component is responsible for processing all incoming HTTP requests. This component is divided into two modules: one handles requests from other microservices for certain actions, and the other opens the event channel.
- Two components of the data warehouse: *AnalyticalDataStore* and *EventStore.* These components are responsible for communicating with the *DataStore*: *EventStore* manages saving events in the *DataStore* and reading them from it; *AnalyticalDataStore* manages reading and updating analytical information in the *DataStore.*

Microservice *Learning Analytics Service* supports the following types of synchronous requests:

1. *Request for student activity assessment*: The microservice analyzes behavioral data (logins, completed tasks, study time, etc.) using input parameters—student ID, time period, platform, and activity type—and outputs the activity level (low, medium, high) (Figure 4)

```
GET / analytics / activity ? studentId = "КІУКІ-22-1(1)" & dateRange =
last_week

…

{
  "studentId": "КІУКІ-22-1(1)",
  "activityLevel": "High"
}
```

Figure 4: An example of querying current student activity (first line) and JSON representation of analysis results (after three points, in curly brackets).

2. *Request for performance forecasting.* The microservice predicts future grades or course completion probability using input data—student ID and course/module list—and outputs performance forecasts (probability of course completion, predicted grade point average) (Figure 5).

```
GET /analytics/performance?studentId="КІУКІ-22-1(1)"&courseId="Microservice
architectures"
…

{
  "studentId": "КІУКІ-22-1(1)",
  "predictedPerformance": 85,
  "completionProbability": 0.92
}
```

Figure 5: An example of a forecasting request (first line) and JSON analysis results.

3. *Request for risk assessment.* The microservice evaluates a student's risk level (high, moderate, low) based on academic performance and activity, providing recommendations. The input: student's ID, historical activity and academic performance data; the output: the risk level and the corresponding recommendations (Figure 6).

```
GET /analytics/risk?studentId="КІУКІ-22-1(1)"
…

{
"studentId": "КІУКІ-22-1(1)"
"riskLevel": "High",
"recommendations": [
   "Increase participation in assignments",
   "Contact tutor for additional support"
   ]
}
```

Figure 6: Example of a risk assessment request and JSON results.

4. *Request for analysis of a group of students.* A query for analyzing a group of students, for example, for teachers or administrators to assess the overall level of activity or risk in the group. The input data is student IDs or group ID; the output data is analytical information for the group of students (average activity level, average academic performance, share of students at risk) (Figure 7).

```
GET /analytics/group-analysis?groupId="КІУКІ-22-1"
…

{
"groupId": "КІУКІ-22-1",
"averageActivityLevel": "Moderate",
"averagePerformance": 76,
"highRiskStudentsCount": 5
}
```

Figure 7: An example of a request to analyze a group of students (first line) and JSON representation of analysis results.

5. *Request to view historical data.* This query allows you to get detailed data on the history of student activity, grades, or risks for a certain period. The input data is the student ID, time period; the output data is historical data on activity, grades or risks for a given period (Figure 8).

```
GET /analytics/history?studentId="КІУКІ-22-1(1)"&dateRange=last_month
…

{
  "studentId": " КІУКІ-22-1(1)",
  "history": [
    {
      "date": "2024-09-30",
      "activityLevel": "High",
      "performance": 78
    },
    {
      "date": "2024-09-01",
      "activityLevel": "Low",
      "performance": 65
    }
  ]
}
```

Figure 8: An example of a request to view historical data (first line) and JSON representation of analysis results.

Microservice *Learning Analytics Service* can support a wide range of synchronous queries. Each of these queries can be used in real time to quickly provide analytical data to help students, teachers, and administrators make effective decisions.

In the future, we plan to expand it by adding more sophisticated machine learning models to more accurately predict student performance or expand the list of behavioral indicators for analysis.

4. Conclusion

The proposed model for individualized learning leverages student behavioral data through analytics, adaptive learning, and decision automation. Key steps include data collection, learning analytics, and personalized adaptation. Important elements of the system are:

- Learning Analytics Engine, which analyzes behavioral data to determine student performance and improve learning paths;
- Adaptive Learning Module, which dynamically adjusts the learning process to individual needs;
- Intelligent Agents that provide progress monitoring and feedback between students and teachers;
- Security and Privacy Module, which guarantees the security and confidentiality of data.

The model is implemented on the basis of a microservice architecture that provides flexibility, scalability, and ease of maintenance. Each microservice is responsible for specific functions, such as data collection, learning analytics, adaptation of the learning process, security, etc. Interaction between microservices is carried out through the API Gateway, which ensures coordination of requests and maintains a single interface for clients.

The proposed model already allows classifying students by activity level and assessing the risk of learning failure. Further development of the system involves the integration of more sophisticated machine learning algorithms to more accurately predict results and add new parameters for analysis.

Thus, the implementation of this system will make it possible to increase the efficiency of the educational process by individualizing learning paths and providing timely feedback, which will contribute to better results for students.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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