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RESEARCH ARTICLE

A conceptual approach to digital transformation of the educational process at a higher education institution

Alexey A. Kytmanov [1, @], Yuliya N. Gorelova [2], Tatiana V. Zykova [3], Olga A. Pikhtilkova [1], Elena V. Pronina [1]

[1] *MIREA – Russian Technological University, Moscow, 119454 Russia*
[2] *Kazan (Volga Region) Federal University, Kazan, 420008 Russia*
[3] *Siberian Federal University, Krasnoyarsk, 660041 Russia*
[@] *Corresponding author, e-mail: kytmanov@mirea.ru*

Abstract
Objectives. The research aims to develop a conceptual approach to the digital transformation of university educational processes. The approach is based on a detailed analysis of the stages, participants, and components of the educational process at universities in order to develop a roadmap for digitalization and the development of a data-driven educational process management system. The main objectives of digital transformation are: (1) improve convenience for all groups of end users by providing access to data and operations with data related to the educational process; (2) increase the transparency of all components of the educational process; (3) release human and time resources by minimizing routine operations and improving the quality of decisions. The development of a data-driven educational process management system is based on digital culture principles of process management, which imply that the data collected in university systems are consistent, organized into a single structure. and stored in a form convenient for the development of new digital services. The development of tools for intelligent decision support and learning analytics is executed cooperatively by developers, analysts, and end users at all levels.
Methods. The research considers the work experience of the authors and their colleagues in Russian and international universities as users of information systems and services, developers of educational analytics services, and managers at various levels, as well as the stages of university digital transformation.
Results. The proposed conceptual approach increases comprehension by setting goals and organizing the planning of digital transformation processes in education. As well as providing a detailed description of the major participants and components of the educational process, comprising students, teachers and educational programs, the article discusses data selection criteria.
Conclusions. The development of a conceptual approach for creating a data-driven educational process management system at a university is becoming a priority task, whose successful execution will underpin further university advancement and competitiveness.

Keywords: digitalization, digital transformation, data-driven management, educational process, student, teaching staff, educational program, learning analytics

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НАУЧНАЯ СТАТЬЯ

Концептуальный подход к цифровой трансформации образовательного процесса в вузе

А.А. Кытманов [1, @], Ю.Н. Горелова [2], Т.В. Зыкова [3], О.А. Пихтилькова [1], Е.В. Пронина [1]

[1] *МИРЭА – Российский технологический университет, Москва, 119454 Россия*
[2] *Казанский (Приволжский) федеральный университет, Казань, 420008 Россия*
[3] *Сибирский федеральный университет, Красноярск, 660041 Россия*
[@] *Автор для переписки, e-mail: kytmanov@mirea.ru*

Резюме

Цели. Целью работы является разработка концептуального подхода к цифровой трансформации образовательного процесса в вузе. В основе выбранного подхода лежит детальный анализ этапов, участников и компонентов образовательного процесса в вузе с целью выработки дорожной карты по его цифровизации и созданию системы управления образовательным процессом на основе данных. Основными задачами цифровой трансформации являются: повышение удобства доступа к данным и работы с данными, относящимися к образовательному процессу, для всех групп конечных пользователей; повышение прозрачности всех составляющих образовательного процесса; высвобождение человеко-временных ресурсов за счет минимизации рутинных операций и повышения качества принимаемых решений. В основе создания системы управления образовательным процессом на основе данных лежат принципы цифровой культуры управления процессами, которые подразумевают, что собираемые в университетских системах данные упорядочены в единую структуру, согласованы между собой, непротиворечивы и хранятся в виде, удобном для разработки новых цифровых сервисов. Разработка инструментов интеллектуальной поддержки принятия решений и учебной аналитики ведется в тесном взаимодействии разработчиков, аналитиков и конечных пользователей всех уровней.

Методы. В работе использован опыт работы авторов и их коллег в российских и зарубежных вузах в качестве пользователей информационных систем и сервисов, разработчиков сервисов учебной аналитики и руководителей разного уровня. Приведены этапы цифровой трансформации организации.

Результаты. Предложен концептуальный подход к пониманию, постановке целей и планированию процессов цифровой трансформации образовательного процесса. Подробно описаны данные основных участников и составляющих образовательного процесса: обучающихся, преподавателей и образовательных программ, необходимые для управления вузом на основе данных; аргументирован их отбор.

Выводы. Разработка концептуального подхода для создания системы управления образовательным процессом на основе данных в вузе становится приоритетной задачей, от качества решения которой во многом будут зависеть развитие и конкурентоспособность университета в будущем.

Ключевые слова: цифровизация, цифровая трансформация, управление на основе данных, образовательный процесс, обучающийся, профессорско-преподавательский состав, образовательная программа, учебная аналитика

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INTRODUCTION

The digitalization of education is an important process aimed at solving problems related to the creation of technologies and the development of services for optimizing the educational process and making it more adequate to the needs of its key stakeholders: students, teachers, employers and graduates [1]. Over the past two decades, a large number of information systems and services have been implemented for collection, storage, and processing of data on participants and components of the educational process [2]. First of all, we mean here learning management systems (LMS), representing platforms for providing teaching and learning materials related to the corresponding courses. Depending on the level of development of teaching and learning materials, as well as the automation of assessment procedures, e-courses hosted on such platforms can serve both as a support for the educational process conducted in face-to-face format and as comprehensive resources within the framework of distance learning [3]. Examples of such systems include intra-university online learning platforms, many of which are Moodle-based[1], as well as Massive Open Online Course (MOOC) platforms, including such well-known platforms as Coursera[2], edX[3], and Udacity[4] (a more detailed list can be found on Wikipedia[5,6]). Such platforms allow for the collection of large amounts of data about learners and their process of mastering educational material. The emergence of such data collection tools has given rise to new areas of research such as Educational Data Mining and Learning Analytics. These fields, which were formalized as distinct areas of research in the early 2000s, have been developing much more rapidly over the past decade. A comparison of these concepts is presented in [4]. The ultimate goal of both processes is the ability to predict learning outcomes based on the analysis of educational platform data, while the focus of Learning Analytics is on the learning process itself and, accordingly, the performance (success) of the learner in mastering the course material. Educational Data Mining focuses directly on the process of extracting information from various sources [5].

A number of studies in the field of Learning Analytics have been related to the creation of systems for predicting learning outcomes based on the analysis of grades received, time spent on assignments, and overall course performance [6]. In addition, learning analytics tools are viewed as a source of real-time information for participants of the educational process (teachers and students). They allow learners to assess their own progress in the course compared to other participants, as well as to plan their time for completing assignments [7].

We note, however, that the potential of such systems is limited, as it is based on student activity data in e-learning courses, which can also be supplemented with attendance and activity data in face-to-face classes [8]. In particular, most existing systems do not take into account learners' individual characteristics such as cognitive style, motivational component, language and cultural aspects. In [9], the author emphasizes that in the digital educational environment, unlike traditional in-class learning, the stakeholders of the educational process have difficulties in determining the level of student engagement and motivation due to the lack of a conceptual approach to the process of modeling, forming, and maintaining student engagement in learning using digital educational resources. Moreover, such systems typically work with intra-disciplinary level data, i.e., data produced by student work activity within the studied course. At the same time, to create a decision support system that functions at the university level, it is necessary to use data from different hierarchical levels (see [10]), since aggregated data used for university statistics often do not reveal the underlying causes of problems arising in the educational process. In addition to students, educational processes involve teaching staff, who provide training and monitoring over the formation of knowledge, skills and abilities, as well as the degree programs (DP) themselves [11].

The present work proposes a conceptual approach to understanding, goal-setting and planning the processes of digital transformation of the educational process to enable the development of intelligent decision support

[1] https://moodle.org/. Accessed January 15, 2024.
[2] https://www.coursera.org/. Accessed January 15, 2024.
[3] https://www.edx.org/. Accessed January 15, 2024.
[4] https://www.udacity.com/. Accessed January 15, 2024.
[5] https://en.wikipedia.org/wiki/List_of_MOOC_providers. Accessed January 15, 2024.
[6] Roskomnadzor: the foreign owner of the resource violates the law of the Russian Federation.

tools. The described approach can serve as a basis for the development of a data-driven educational process management system.

1. METHODS

The study is based on the experience of the authors and their colleagues in Russian and international universities as users of information systems and services, developers of learning analytics services, and managers at different levels (teachers, e-course developers, academic heads of the educational program, department heads, school deans, heads and deputy heads of student affairs, developers of student success forecasting models, heads of IT departments, etc.). In addition, we study the global research experience in the fields of Digitalization in Education, Learning Analytics, and Educational Data Mining.

The following section describes the stages of digital transformation of the organization to provide a more informed vision of the roadmap and planning of activities for digitalization of the educational process. Its main objectives are to increase the transparency of all components of the educational process and subprocesses within it, minimize the routine burden on the participants of the educational process, and optimize the educational process by improving the quality of decisions taken at different levels. One of the main goals of digital transformation of an educational organization is to create a data-driven educational process management system as a set of Learning Analytics tools providing intelligent decision-making support.

2. STAGES OF THE DIGITAL TRANSFORMATION

The digital transformation of an organization is based on its level of digital maturity, representing an awareness of the need to transform its core processes related to data acquisition and information exchange. At the initial level of digital maturity, such transformations are spontaneous and typically initiated by individual departments as a means of optimizing their internal processes. A high level of digital maturity implies the consistent implementation of activities for the coordinated transformation and integration of all key processes of the organization in accordance with the developed transformation strategy and roadmap. As shown in the figure below, the digital transformation of an organization can be divided into three main stages.

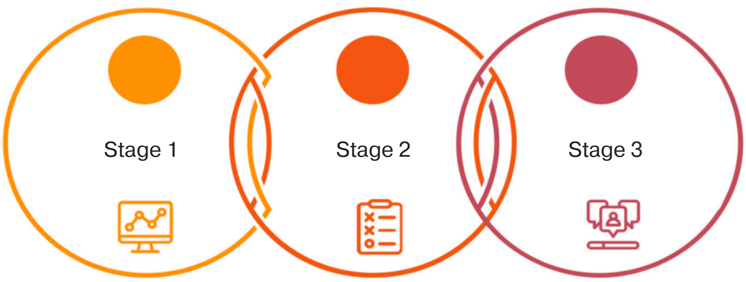
2.1. Organization of work with data in digital form

The main disadvantage of document flow on physical media is the high labor intensity of their verification, statistical processing, analysis, and, as a consequence, decision-making based on the information extracted from them. Here, an acute problem arises in terms of accessing data from past periods, for example, for the preparation of reports or visualization of achievements over time.

When implementing electronic document or file management systems at this stage, a critical feature is the availability of data export tools in widely used formats, as well as options for presenting data in various formats, in particular, for the creation of summary forms and reports. In other words, one of the important criteria for the usability of the abovementioned systems and services is the availability of tools that provide flexibility in working with data. An example that illustrates the actual absence of document digitization is the storage of scanned versions of previously printed documents within the system.

2.2. Technological optimization of processes

The next step in digital transformation involves changing the methods of working with data and organizing interactions between departments based on



Organization of the work with data in a digital form
- Data export opportunity
- Generation of forms and reports
- Storage of documents in scanned form

Technological optimization of processes
- Introduction of new forms of work
- Change in interaction between subdivisions
- Increase in process transparency

Digital culture of process management
- Unified data structure
- Ability to connect new modules
- Module update based on user feedback

Figure. Stages of the organization's digital transformation new working methods and tools to enhance process transparency and release human resources. An example of the transition to this stage is the optimization of the reporting process by automating the collection of data required for a specific type of reports throughout the reporting period. The results of an employee's or team's work during the reporting period should ideally be entered into the appropriate system as they arise. In this case, preparing a report does not require special efforts, since the process itself automates the generation of summarized data on outcomes achieved over a certain period. The approaches used at this stage not only save human resources but also significantly increase process transparency and reduce the likelihood of providing inaccurate data.

2.3. Transition to a digital culture of process management

At this stage, all key processes of the organization's functioning should comprise parts of a single whole. All collected data should be organized into a unified and coordinated structure to organically complement each other. As described in detail in [10], information systems function on the basis of database(s) designed to take into account the principles of student-centeredness, data continuity, and data consistency. Compliance with these principles when designing and developing the digital infrastructure of the university guarantees consistency and the absence of conflicts in data when working across different systems. It also guarantees completeness by storing all data with timestamps that allow for the accurate reconstruction of a learner's educational history, as well as providing ease of use. The information systems should allow for the connection of new modules and be updatable based on feedback from end users. The development of new modules and services is carried out in close cooperation between developers, analysts, and end users at all levels: top and middle managers, student affairs staff, as well as representatives of teaching staff and students. This digital infrastructure facilitates the development of data-driven learning analytics and decision support tools for more effectively identifying issues in the learning process and finding their possible solutions.

3. RESULTS

In this section, the main participants and components of the educational process (hereinafter subjects or objects of the educational process) are considered: students, teachers and DPs. The data structure for each subject (or object) is proposed and its detailed description is given in the context of the concept and objectives of data-driven management. The more information can be collected, the more clearly it can be structured and described in detail, resulting in higher system potential.

3.1. Student data

Since the student is a key participant in the educational process, it becomes especially important to initially classify his or her data in such a way that their subsequent use will simplify the process of data extraction and analysis [12]. When building a model of a student, two types of data should be taken into account: (1) the data that do not change or change very slowly over time (socio-demographics, gender, age, nationality and cultural characteristics, psychological characteristics and cognitive features, etc.); (2) accumulated data on the process and results of learning (accumulated digital footprints (entrance examination scores, results of participation in academic competitions, secondary education certificate grades, data on his or her activity on educational platforms) comprising a student's digital educational history, the concept of which was introduced in [13].

One of the important tasks of Learning Analytics is modeling the student, including the creation of his or her digital twin. It is clear that the more data about the student and his or her learning process can be collected, the more accurate the learner model will be. In particular, an important task is developing tools for collecting data on student's use of learning materials from external sources (educational content, educational forums, various reference materials).

When collecting data, it is important to adhere to the principle of data continuity [10] to ensure that no data that changes over time is lost, in particular, in the process of updating (overwriting). For example, in case a student does not pass an exam at the first attempt, all dates and results of attempts should be stored in the database. This gives a more comprehensive picture of academic performance, helping to identify problems with learning in a timely manner and adjust personal learning trajectories. In cases when a student switches from one major (degree program) to another, such changes in the student's interests or difficulties in mastering certain courses should also be recorded. In other words, such indicators can be used to identify and address problem areas with subsequent adjustment of the DP in order to improve its quality.

We will conditionally divide all data into three groups. The first group includes general data used in educational and administrative processes. The second group operates with data related to a specific DP and its learning outcome requirements. Finally, the third group contains information about the student's activity and performance in a particular course of the DP.

The first block includes *basic data on the student*:
- basic personal data,
- socio-demographics,
- health records,
- admission data,
- academic status of the student.

Basic personal data contains the student's surname, first name, patronymic, date and place of birth, gender, data on main identification documents (passport, social security number, taxpayer identification number).

Socio-demographic data includes information on marital status, family members, as well as the number of dependents and average income. This information may prove useful when considering the possibility of applying for social scholarships and other assistance.

Health records form an important basis for determining whether inclusive education is necessary. This includes data on the presence of medical conditions and the opinions of medical experts.

Admission data traditionally include entrance examination scores or results of previous final attestation, as well as the results of participation in academic competitions, which confer certain privileges when applying for the next level of education. An applicant's portfolio data can give additional points at admission to some areas of training. At admission to a Master's program, information about the student's bachelor's diploma, results of entrance examinations, as well as publication record, will be required.

Academic status contains information about the current status of the student, e.g., studying / completed training / on academic leave / expelled / in the process of readmission. It can also indicate the status of the student in the educational context, namely, information about courses mastered within the framework of the DP, attained internships, internships, supervisors, the topic of a graduation thesis, etc.

These data can be supplemented with data on a student's psychological characteristics, cognitive features and styles. Taking into account such student characteristics can be useful in planning and organizing his educational and extracurricular activities, for example, when designing a personalized learning path.

The second group contains the following data blocks of interim and final attestation, as well as pre-professional training of student:

Data block for *intermediate and final assessment:*
- results of intermediate assessment for all years of study;
- term exams results;
- amount of academic debts at the present moment;
- number of attempts to pass the assessment for the course.

Pre-professional training data block*:*
- topics of completed research works and data on scientific advisors;
- research publications;
- conference presentations and talks;
- experience in professional activity in organizations relevant to the field of study;
- reviews and feedback on research and graduation theses;
- experience in team projects/startups participation with record on personal contribution.

The intermediate assessment section can provide useful information about the most challenging courses for students and help to select the appropriate educational materials, taking into account their background in the field of study, motivation and ambitions. Based on such data, it is possible to create more advanced services, such as services for predicting the student's success in completing an educational program or recommendation systems [14], which can build a personalized learning path depending on preferences, abilities and previously accumulated information about the user (digital footprints and digital educational history).

The research interests of the student and his or her readiness for research activity can be judged based on pre-professional training data. This is important when choosing a base for internships, or selection of potential job places for future graduates. Data on the scientific supervisor, reviews and feedback can provide students with guidance on choosing research topics, the relevance of these topics, and prospects for further development or career opportunities in the science and technology sector.

We move on to the third group of data comprising educational course data. This includes:
- number of accesses to the LMS and total time spent in it;
- number of transitions and number of clicks within the LMS;
- number of viewed educational videos and their viewing duration;
- participation in discussions on educational forums;
- number of references to external educational sources, total time spent on mastering educational material;
- success in completing assignments (accuracy, timeliness, independence level).

The data of the third group characterize the student's performance within a particular course. Currently, most educational courses are presented in electronic form in the university LMS (typically Moodle-based; a detailed list of LMS can be found on Wikipedia[7,8]). Course structure,

[7] https://en.wikipedia.org/wiki/List_of_learning_management_systems. Accessed January 15, 2024.

[8] Roskomnadzor: the foreign owner of the resource violates the law of the Russian Federation.

the content of assessment materials, evaluation criteria, and deadlines for assignments are generally determined by the course instructor on the basis of the approved course syllabus.

The course instructor, using access to the event log and gradebook, can obtain data on the student's activity within the course. It is also possible to get such data as study time, number of accesses to educational materials, educational video viewing time, and results of interim testing. In future, it will be possible to use these or other indicators to track the dynamics of academic performance within a course.

To summarize, the data in the first group usually remain unchanged or change slowly over time, while the data of the second group are updated on a regular basis, typically at least once per academic term. The data of the third group are updated most frequently, usually weekly.

3.2. Data on tertiary teachers (course instructors)

The next key subject of the educational process is the teacher, whose qualifications, experience and pedagogical skills largely determine the effectiveness of knowledge delivery and consequent effectiveness of the educational process. The author's interpretation of a particular course in the curriculum influences the motivation of students and their involvement, knowledge and skills gained as well as the learning outcomes of the course [15]. Unlike student data, on which most researchers of learning analytics are focused, the exploration of teacher data has drawn much less attention. However, interest in this topic has recently started to grow (see, for example, [16]).

Teachers undergo regular performance appraisals, for example, as part of employment or competitive election. For this procedure, the applicant prepares a list of his or her achievements for a certain period in the form approved by the organization where he/she plans (to continue) to work. However, data submitted in this way may contain inaccuracies; for example, there may be errors in their design. Most importantly, such data are usually used once and are not stored for future use. In addition, the preparation of such reports is time-consuming and routine. On the other hand, a properly organized data collection on the teacher's achievements in different areas will make it possible to receive such reports automatically without time and labor costs, while significantly reducing the risks of inaccurate or erroneous information. From a manager's point of view, a digital service for working with faculty data can provide opportunities to monitor the achievements not only of an individual employee, but also to generate summary reports on teams (employees of a department, institute, members of a scientific team) or groups (3rd-year students, PhDs under the age of 35, etc.), as well as the dynamics of employee- or team achievements over a certain period.

For the convenience of assessment, monitoring and timely adjustment of the educational process in the context of the teacher, it is proposed to consider the data on the teacher by analogy with that of students as multidimensional, structured, dynamically updated data on professional competence, communication skills, as well as digital competence and digital culture, including a group of personal data and groups of indicators. Each indicator is considered with respect to the information that can be obtained in the current moment—static data and dynamic data changing over time under the influence of some external factors, experience, or issued recommendations.

The first block of data contains *basic personal and professional information*:

- basic personal data (surname, name, patronymic, date and place of birth, gender, data of basic documents);
- socio-demographic data (marital status, family members, average income);
- health data (in relation to labor duties);
- data on education, academic degrees and titles;
- data on previous employment and positions held;
- data on mother-tongue and foreign language proficiency;
- data on teaching experience;
- profile data in scientometric databases and professionally-oriented social networks.

This block, which contains a standardized set of data that does not change or changes slowly over time, can be used to form a picture of the main stages of work history, e.g., relating to periods of employment.

The following blocks describe the teacher's competence as researcher, mentor, or practitioner.

The *teaching and learning competence* data block contains:

- data on courses taught (linked to academic years and semesters, indicating the type of classes and form of delivery);
- data on the number of students in the courses taught;
- data on developed teaching and learning materials and e-courses;
- data on external resources used in teaching practice;
- developed information content used in teaching activities;
- data on completed professional development / retraining / vocational training courses;
- data on student assessment of the teacher (if available);
- student attendance in the course during the semester;
- student academic performance within the course and the results of the term exam.

The *scientific research competency* data block includes:

- data on publications and intellectual property objects;
- data on participation in projects supported by research grants or carried out within the framework of contractual works, as a manager or contractor;
- data on membership in dissertation councils, editorial boards of scientific journals;
- data on work performance as an expert.

The *mentoring competency* data block contains:

- data on scientific supervision of graduation theses / dissertations of students / master's degree students;
- data on scientific supervision of postgraduate students / scientific advising of doctoral students;
- data on publications of students/postgraduate students co-authored with an academic staff member;
- data on graduation theses / candidate/doctoral dissertations, defended under the supervision of an academic staff member;
- data on students/postgraduate students who won prizes in competitions/contests/conferences (with indication of the event level).

The *practical competence* data block includes:

- data on work experience in organizations/enterprises in the field of training in which the teaching is provided (indicating places of work, positions held, main duties performed);
- data on developed cases drawn from practical experience;
- data on practice-oriented tasks developed for competitions/hackathons;
- data on expert experience in the professional field.

In addition to these blocks, it is also appropriate to introduce an additional data block, where an employee could provide other information indicating his or her professional qualifications, for example, awards received, competitions won, interuniversity and international team participation, consortia, organization of events, presentations of popular science lectures, experience in preparing and conducting trainings, business games, etc. These data can be subsequently classified into separate blocks to facilitate their effective application.

These blocks can be supplemented by a block of communicative and other soft skills, which can include the ability to deliver the course according to the audience preparation and proficiency (adaptability), motivation building and critical thinking skills, the ability to build productive interpersonal relationships within the team. However, it should be noted that the measurement of such skills requires special consideration. The level of communicative competence can be evidenced, for example, by the results of student evaluation of the instructor, the number of co-authors in publications, or participation in collective projects.

The block of teacher digital competence and digital culture requires a separate detailed exploration. It needs to consider the proficiency of using various digital tools in teaching and research, as well as the acceptance of changes brought by digitalization and the readiness to implement these changes. As faculty digital culture is an integral part of the corporate culture, its development becomes a significant issue of change management in the university.

A data collection and storage system should be capable of automatically retrieving data as they become available. An example is the retrieval of data from scientific metrics systems on published articles. Where automatic retrieval is impossible, the system should provide standardized data entry with supporting documents or references.

3.3. Degree program data

DP is one of the most significant components of the educational process and its quality directly affects its popularity among students and applicants. Insufficiently high indicators of the educational process (e.g., low academic performance, high percentages of students who change a DP over the course of training, low employment rates) can represent the evidence not only of insufficiently trained students, but also problems with the program itself. The most acute of these is the low demand for the program during the admission campaign and consequently low competition among the applicants. This could result in enrollment of students with lower exam scores who tend to be less motivated. This, in turn, entails further problems with their learning within the program. Low demand for DP typically has two reasons behind it: external (obsolescence, i.e., insufficient compliance with the changing demands of the labor market) and internal (inconsistency of the content and structure of the program with the stated learning outcomes). Despite the fact that the educational community—including DP developers themselves—recognizes the existence of the mentioned problems, there is currently no methodology to clearly describe an algorithm for DP analysis and evaluation, as well as identifying its weaknesses and correcting them.

In this regard, it is important to define a set of internal DP indicators for characterizing the features of its structure and content, as well as external DP indicators, which form a basis for judging DP quality and demand. Each indicator then needs to be associated with a set of data on which basis it will be calculated.

The main *internal characteristics* of the DP can be considered as follows:

- field of study, including level of education, form of education;

- requirements of the federal state educational standard or the educational standard of the educational organization, including learning outcomes expressed in term of competencies;
- professional standards, for which the DP trains students, including formed professional competencies;
- the structure of an DP, defined by its curriculum and including a set of disciplines and practices, as well as their labor intensity and mastering schedule;
- DP development team;
- Personnel implementing the DP;
- material and technical support for the DP;
- other characteristics, such as involvement of employer representatives in the learning process, availability of real-life tasks (cases) adapted to the learning process, geography range of internship sites, etc.

These characteristics, which determine the design, structure, and content of the DP, have a direct impact on its quality. However, in order to assess the quality of the DP, it is necessary to evaluate external indicators independent of its internal content, as they indicate how much external stakeholders (graduates, their employers, various administrative bodies of regional and federal levels) are satisfied with DP quality.

Among the main *external indicators* characterizing the quality of a DP, we note the following:

- distribution of Unified State Exam scores of applicants admitted to the DP, including their average and passing scores;
- proportion of entrants to the DP who have particular achievements (winners and prize-winners of academic olympiads and competitions at various levels);
- indicators related to the results of the intermediate certification: grade distribution records by course within a specific term / examination period, dynamics of the proportion of students who have a certain level of academic debt, etc.;
- student academic status updates: dynamics of dropout rates, academic leaves, changes of degree program (major) or higher education institution, dynamics of re-enrollments, transfer to DPs from other DPs within the university, from other universities, etc.;
- share of students (by year of study) who have achievements in research activity (presentations at scientific conferences, publications, intellectual property objects);
- share of students (by year of study) who have achievements in professional activities, noted by potential employers as a result of internships, participation in project work, case studies, etc.;
- employment rate of graduates in organizations relevant to their field of study;
- results of surveys of students regarding their satisfaction with the components of the educational process within the DP;
- results of surveys of graduates regarding their satisfaction with training within the DP, employment opportunities, competitiveness in the labor market, etc.;
- results of surveys of employers regarding their satisfaction with the qualification of graduates, interaction with the university, development team, course instructors implementing the DP.

Note that the development of a methodology for working with the above indicators requires special attention, since their absolute values (as they are) do not carry much meaning in terms of determining the quality of DP. The following approaches can prove useful

- consideration of these indicators in dynamics over a certain period of time;
- consideration of relative values of the indicators compared to similar indicators from other degree programs within one or similar groups of fields of study within the university;
- consideration of relative values of the indicators compared to similar indicators of degree programs in the same field of study at other universities, ranging from the nearest regional competitors to all universities in the country implementing programs in this field.

The development of methods for analyzing and assessing the quality of degree programs, as well as identifying their strengths and weaknesses, is a distinct and under-researched field of study. The very definition of the quality of a degree program is an important task in itself. We suggest that the quality of a degree program be defined in terms of achieving the desired learning outcomes, expressed in terms of competencies a graduate should possess upon successful completion of the program. However, measuring the level of possession of competencies, or professional skills of graduates are nontrivial tasks that do not have a straightforward solution. It should also be understood that a degree program is not an unchanging set of documents, but rather a dynamically evolving entity that connects students, faculty and teaching staff, administrative personnel, employer representatives, and other stakeholders within the educational process. As a key component of the educational process, DP is an important object of study within the framework of data-driven educational process management. In the context of a rapidly changing labor market, the tasks of creating tools for analyzing DPs, managing and optimizing their portfolio within the university are highly relevant.

4. DISCUSSION

Processes of digitalization in higher education institutions are currently implemented mainly through the creation of specialized systems and services which function within particular areas and are aimed at solving a limited range of tasks [17]. One of the main disadvantages of this approach is that such services usually do not include protocols of interaction with each other, since their operation is often based on data stored in databases specially designed for these systems. This leads to the problems described in [10], namely, data duplication and redundancy, as well as absence of unified storage standards and consequent conflicts in data exchange between different information systems. The inability to integrate these systems as components of a coherent whole presents a challenge to addressing higher-level objectives, such as, for instance, determining the root causes of a decline in student retention rate in a given DP or the increase of student attrition from that program and their subsequent enrollment in other programs. We believe that the use of a single information platform, referred to as the "core", which instantiates the principles for data collection, storage, and processing for all university information systems, can help address the aforementioned challenges. Such systems would represent modules connected to the core. In addition, the sequential connection of new modules, modified according to end user requests, will significantly improve the transparency of internal processes, reduce labor and time expenditures, and increase the speed and accuracy of decision-making.

It should be noted that the core data elements of students, faculty, and DPs discussed in this work are interconnected in numerous ways. For example, the outcomes of a student's mid-term assessment in a subject are not solely determined by the student themselves, their motivation, level of preparation, and assignments completed during the term. Rather, they depend on the qualifications of the teachers who taught this subject, and the level of their expectations, methods, formats, teaching materials, as well as the structure of the course (in particular, the total workload and the distribution of workload between contact hours and independent study), as outlined in its syllabus. Additionally, if the course content is based on knowledge gained in other subjects of the educational program, then the structure of the course, as determined by the curriculum, also plays a significant role. In practice, there are instances where the skills and knowledge acquired by students in one subject are applied in another, with both subjects being taught concurrently in a single semester, which can create understandable challenges for students. Thus, the purpose of data-driven educational process management is to, among other things, simplify the process of accessing a diverse range of data related to the education process as much as possible, and to develop data analysis and visualization tools to facilitate the identification of areas for improvement in the educational process with a view to further optimizing it.

The next significant consideration is that the development, customization, and technical maintenance of such a system must be undertaken throughout its entire lifecycle. Both the development and subsequent refinement or modification of individual modules should occur in close collaboration with end users, based on the systematic collection of feedback. Having a team consisting of representatives from various roles, including developers, technical support personnel, senior management, and representatives from all groups of users and stakeholders, can help to make the process of evolving such a system more effective. In addition, it is essential that the process of gathering feedback and making subsequent changes to the system is regular and timely. Otherwise, the positive impact of the process may be significantly diminished, which could in turn negatively affect the overall effectiveness of the system. In this regard, using proprietary software developed by third-party vendors may offer less practical benefit to the organization compared to developing its own software in-house by a dedicated team of developers.

Finally, we would like to highlight another aspect that plays a crucial role in the successful implementation and development of a data-driven educational process management system. This aspect involves the adoption of the system by all relevant stakeholders and their willingness to contribute to its improvement and enhancement. The introduction of such a system has the potential to significantly enhance the transparency of various aspects of an employee's performance, which may lead to at least a mixed reaction towards the system and decisions made based on data generated by it. A very important point here is the interpretation of the data and indicators obtained. In view of the above, building a system of decision-making in relation to participants in the education process in the context of rewarding them for their achievements and supporting them in eliminating problem areas and realizing potential points of growth will be an important component of the successful implementation and further development of such a system.

CONCLUSIONS

In the present article, we propose a conceptual approach to the digitalization of the educational process in a higher education institution, describing its main stages, as well as providing data blocks for the key participants and components of the educational process: students, teaching staff and DPs. We highlight certain features and challenges associated with the development and implementation of information systems and digital services for building a data-driven educational process management system.

In subsequent works, the authors plan to study in detail each component of the proposed conceptual approach, analyzing the specifics of collecting and assessing indicators related to students, teaching staff, and DPs.

Digitalization of the educational process represents an essential stage in the development of a university, without whose implementation it will be impossible to reach a significantly new level of educational activity. The continuously growing market of educational services, especially in terms of continuing professional education, puts universities in a position of catching-up as compared to online educational platforms, which have significantly excelled in the use of digital tools for Learning Analytics. Consequently, the development of a conceptual approach to create a digital system of educational process management in the university becomes a priority task, the quality of which will greatly influence the future development and competitiveness of the university.

Authors' contributions

A.A. Kytmanov—conceptualization, methodology, writing (original draft preparation, review, and editing), supervision.

Yu.N. Gorelova—formal analysis, writing (original draft preparation, review, and editing).

T.V. Zykova—methodology, formal analysis.

O.A. Pikhtilkova—formal analysis, writing (original draft preparation).

E.V. Pronina—formal analysis, writing (original draft preparation).

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About the authors

Alexey A. Kytmanov, Dr. Sci. (Phys.-Math.), Head of the Department of Higher Mathematics – 3, Institute for Advanced Technologies and Industrial Programming, MIREA – Russian Technological University (78, Vernadskogo pr., Moscow, 119454 Russia). E-mail: kytmanov@mirea.ru. Scopus Author ID 6602129708, RSCI SPIN-code 6866-6079, https://orcid.org/0000-0003-3325-099X

Yuliya N. Gorelova, Cand. Sci. (Phil.), Head of the Master's Center, Institute of Management, Economics and Finance, Kazan (Volga Region) Federal University (18, Kremlevskaya ul., Kazan, 420008 Republic of Tatarstan, Russia). E-mail: JNGorelova@kpfu.ru. Scopus Author ID 56521686700, RSCI SPIN-code 9505-0346, http://orcid.org/0000-0003-1114-9751

Tatiana V. Zykova, Cand. Sci. (Phys.-Math.), Assistant Professor, Department of Applied Mathematics and Data Science, School of Space and Information Technology, Siberian Federal University (79, Svobodnyi pr., Krasnoyarsk, 660041 Russia). E-mail: tzykova@sfu-kras.ru. Scopus Author ID 57188699496, RSCI SPIN-code 1959-9769, https://orcid.org/0000-0002-7332-2372

Olga A. Pikhtilkova, Cand. Sci. (Phys.-Math.), Associate Professor, Department of Higher Mathematics – 3, Institute for Advanced Technologies and Industrial Programming, MIREA – Russian Technological University (78, Vernadskogo pr., Moscow, 119454 Russia). E-mail: pihtilkova@mirea.ru. RSCI SPIN-code 5589-7411, https://orcid.org/0009-0004-4632-5158

Elena V. Pronina, Cand. Sci. (Phys.-Math.), Assistant Professor, Department of Higher Mathematics – 3, Institute for Advanced Technologies and Industrial Programming, MIREA – Russian Technological University (78, Vernadskogo pr., Moscow, 119454 Russia). E-mail: pronina@mirea.ru. RSCI SPIN-code 3391-3440, https://orcid.org/0000-0002-2447-7175

Об авторах

Кытманов Алексей Александрович, д.ф.-м.н., доцент, заведующий кафедрой высшей математики – 3, Институт перспективных технологий и индустриального программирования, ФГБОУ ВО «МИРЭА – Российский технологический университет» (119454, Россия, Москва, пр-т Вернадского, д. 78). E-mail: kytmanov@mirea.ru. Scopus Author ID 6602129708, SPIN-код РИНЦ 6866-6079, https://orcid.org/0000-0003-3325-099X

Горелова Юлия Николаевна, к.фил.н., доцент, заведующий центром магистратуры, Институт управления, экономики и финансов, ФГАОУ ВО «Казанский (Приволжский) федеральный университет» (420008, Россия, Республика Татарстан, Казань, ул. Кремлевская, д. 18, корп. 1). E-mail: JNGorelova@kpfu.ru. Scopus Author ID 56521686700, SPIN-код РИНЦ 9505-0346, http://orcid.org/0000-0003-1114-9751

Зыкова Татьяна Викторовна, к.ф.-м.н., доцент, кафедра прикладной математики и анализа данных, Институт космических и информационных технологий, ФГАОУ ВО «Сибирский федеральный университет» (660041, Красноярск, пр. Свободный, д. 79). E-mail: tzykova@sfu-kras.ru. Scopus Author ID 57188699496, SPIN-код РИНЦ 1959-9769, https://orcid.org/0000-0002-7332-2372

Пихтилькова Ольга Александровна, к.ф.-м.н., доцент, кафедра высшей математики – 3, Институт перспективных технологий и индустриального программирования, ФГБОУ ВО «МИРЭА – Российский технологический университет» (119454, Россия, Москва, пр-т Вернадского, д. 78). E-mail: pihtilkova@mirea.ru. SPIN-код РИНЦ 5589-7411, https://orcid.org/0009-0004-4632-5158

Пронина Елена Владиславовна, к.ф.-м.н., доцент, кафедра высшей математики – 3, Институт перспективных технологий и индустриального программирования, ФГБОУ ВО «МИРЭА – Российский технологический университет» (119454, Россия, Москва, пр-т Вернадского, д. 78). E-mail: pronina@mirea.ru. SPIN-код РИНЦ 3391-3440, https://orcid.org/0000-0002-2447-7175

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