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АНАЛІТИКА НАВЧАННЯ І ЦИФРОВИЙ ЗВОРОТНИЙ ЗВ'ЯЗОК У СИСТЕМІ УПРАВЛІННЯ ОСВІТНІМ ПРОЦЕСОМ

У статті обґрунтовано роль аналітики навчання і цифрового зворотного зв'язку в управлінні освітнім процесом. Актуальність дослідження зумовлена тим, що цифрові освітні системи накопичують значні обсяги даних про результати, активність, дотримання термінів, характер помилок і взаємодію здобувачів освіти, однак ці дані часто використовуються переважно для обліку та контролю. Метою статті є обґрунтування взаємозв'язку між аналітичними показниками навчальної діяльності, їх педагогічною інтерпретацією, формами цифрового зворотного зв'язку та можливими управлінсько-педагогічними рішеннями. Дослідження має теоретико-аналітичний характер. Застосовано методи аналізу, порівняння, узагальнення, систематизації та структурно-логічного конструювання. Проаналізовано праці з аналітики навчання, освітнього майнінгу даних, прогнозування академічної успішності, інформаційних панелей, автоматизованого зворотного зв'язку, саморегульованого навчання та використання штучного інтелекту в освіті. У результаті виокремлено основні групи показників, що можуть використовуватися для моніторингу освітнього процесу: академічні результати, активність у системі управління навчанням, своєчасність виконання завдань, характер помилок, участь у взаємодії, динаміка прогресу та використання навчальних ресурсів. Визначено інформаційну, коригувальну, прогностичну, рекомендаційну, рефлексивну й управлінську функції цифрового зворотного зв'язку. Основним результатом є матриця, що поєднує аналітичний показник, його можливу педагогічну інтерпретацію, форму цифрового зворотного зв'язку та відповідне управлінсько-педагогічне рішення. Показано, що цифрові сліди не дають підстав для однозначного встановлення причин навчальної поведінки, тому матриця має орієнтовний характер і не замінює професійного судження викладача. Її практична придатність полягає в можливості використання показників, доступних у стандартних звітах LMS, електронних журналах і системах тестування, без залучення складних прогностичних алгоритмів. Перспективи подальших досліджень пов'язані з емпіричною апробацією матриці в різних дисциплінах і форматах навчання.

Ключові слова: *аналітика навчання, цифровий зворотний зв'язок, управління освітнім процесом, освітні дані, система управління навчанням, педагогічне рішення, моніторинг навчальної діяльності, персоналізований зворотний зв'язок, цифрові сліди, штучний інтелект.*

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LEARNING ANALYTICS AND DIGITAL FEEDBACK IN EDUCATIONAL PROCESS MANAGEMENT

The article substantiates the role of learning analytics and digital feedback in educational process management. The relevance of the study is determined by the fact that digital educational systems accumulate substantial amounts of data on learning outcomes, activity, compliance with deadlines, patterns of errors, and learner interaction, yet these data are often used mainly for recording and control. The aim of the article is to substantiate the relationship between analytical indicators of learning activity, their pedagogical interpretation, forms of digital feedback, and possible managerial and pedagogical decisions. The study is theoretical and analytical. The methods of analysis, comparison, generalization, systematization, and structural-logical construction were applied. Research on learning analytics, educational data mining, prediction of academic performance, learning analytics dashboards, automated feedback, self-regulated learning, and artificial intelligence in education was examined. The study identified the main groups of indicators that may be used to monitor the educational process: academic outcomes, activity in a learning management system, timely completion of tasks, error patterns, participation in interactions, progress dynamics, and the use of learning resources. The informational, corrective, predictive, recommendation-oriented, reflective, and managerial functions of digital feedback were specified. The main result is a matrix that links an analytical indicator, its possible pedagogical interpretation, a form of digital feedback, and an appropriate managerial and pedagogical decision. The study shows that digital traces do not provide sufficient grounds for unambiguous conclusions about the causes of learning behavior. Therefore, the matrix is indicative and cannot replace a teacher's professional judgment. Its practical applicability lies in the ability to use indicators from standard learning management system reports, electronic gradebooks, and testing systems without employing complex predictive algorithms. Further research should include the empirical testing of the matrix across different academic disciplines and learning formats.

Key words: *learning analytics, digital feedback, educational process management, educational data, learning management system, pedagogical decision, learning activity monitoring, personalized feedback, digital traces, artificial intelligence.*

Problem Statement. Digital educational systems collect large amounts of data about results, activity, deadlines, error patterns, and interaction of learners. However, the presence of such data does not guarantee that they are used to improve the educational process. Very often, these data perform mainly a recording function and are used to control attendance, task completion, and final assessment. Learning analytics makes it possible to use digital traces to identify learning difficulties, predict risks, and support pedagogical strategies for solving them [1; 2; 8]. Its managerial value appears when an analytical indicator becomes a basis for a concrete action. Low activity, repeated mistakes, or missed deadlines do not, by themselves, change the learning situation. A pedagogical interpretation of the data, targeted digital feedback, and a relevant teacher decision are needed.

Learning analytics, digital assessment, and feedback are often studied separately. Researchers describe prediction algorithms, dashboards, and automated messages in detail [3; 12; 14], but they explain less clearly how a specific indicator should be linked to a particular response. As a result, a gap appears between data collection and pedagogical action.

Therefore, it is necessary to systematize the links among an indicator of learning activity, its possible interpretations, digital feedback, and managerial and pedagogical decisions. Such systematization allows us to consider learning analytics not only as a technical tool for monitoring, but also as an instrument for managing the educational process.

Analysis of Current Research. Modern studies of learning analytics cover the collection and interpretation of digital data, the prediction of academic performance, the early identification of risks, the visualization of progress, and the support for self-regulated learning. Shafiq et al. [13] and Yağcı [15] confirm the possibilities of educational data mining and machine learning for predicting learning outcomes. At the same time, an algorithmic prediction cannot directly become a pedagogical decision, because the same indicators may have different causes.

Learning analytics dashboards are a separate research area. Bodily and Verbert [3], Susnjak et al. [14], and Paulsen and Lindsay [12] state that dashboards primarily display already recorded results and activities, but they do not always provide a clear path for further action. According to Kaliisa et al. [9], access to a dashboard itself does not guarantee better achievement or motivation. The effect depends on how clear the data are, how they are presented, and whether the information can be used.

Banihashem et al. [2] analyzed the connection between learning analytics and digital feedback. Analytical data can make feedback more timely and personalized, help identify typical mistakes, and recommend further actions. However, receiving a message does not mean that the learner understands and uses it. The quality of feedback depends on whether it helps the learner understand the problem and correct further work [4; 5; 7; 10].

The automation of feedback is closely connected with artificial intelligence. Intelligent systems can classify errors, predict risks, and form personalized recommendations [6]. At the same time, their use creates risks of wrong interpretation, algorithmic bias, low transparency, and excessive automation. For this reason, the teacher's professional decision remains necessary. Ethical limits of using artificial intelligence in education should also be considered [11].

The analysis of publications shows that sources of educational data, prediction methods, and forms of digital feedback have been studied quite fully. The connection between a concrete analytical indicator, its pedagogical interpretation, the content of a message, and the next teacher's decision is still less developed. This creates the need for a matrix that systematizes possible transitions from educational data to pedagogical action.

Aim and Methods of the Study. The aim of the article is to explain the role of learning analytics and digital feedback in educational process management and to develop a matrix that connects analytical indicators of learning activity, their pedagogical interpretation, forms of digital feedback, and possible managerial and pedagogical decisions.

The study is theoretical and analytical. Its source base included scientific publications on learning analytics, educational data mining, prediction of academic performance, dashboards, formative assessment, automated feedback, self-regulated learning, and the use of artificial intelligence in education.

The methods of analysis, comparison, generalization, and systematization were used. The analysis helped to identify the main research areas and determine which types of educational data are most often used to assess activity, progress, engagement, and the risk of academic failure. Comparison was used to distinguish descriptive, diagnostic, predictive, and recommendation analytics, as well as informational, corrective, predictive, and reflective feedback. Generalization was used to define common features of digital tools that support the monitoring of learning activity and pedagogical decisions. Systematization enabled indicators to be organized into 7 groups: academic results, learning activity, meeting deadlines, error patterns, participation in interactions, progress dynamics, and use of learning resources.

The matrix was developed according to the principle of a step-by-step transition from data to a pedagogical decision. First, an analytical indicator that can be recorded by a digital system was defined. Then, a possible pedagogical interpretation of this indicator was identified. After that, a form of digital feedback was selected. This feedback could be addressed to a learner or a teacher. The final component was a managerial and pedagogical decision aimed at correcting learning activity, providing additional support, or changing the organization of the educational process. The developed matrix is not universal and does not replace the teacher's professional decision. Its purpose is to organize possible responses to data and support a reasoned choice of pedagogical action/

Research Results. The analysis showed that learning analytics receives managerial value only when digital data are used for pedagogical interpretation, feedback, and decision-making. Without this connection, analytical tools mainly perform a recording or control function.

The main groups of indicators for monitoring the educational process include academic results, activity in the learning management system, timely completion of tasks, error patterns, participation in interactions, progress dynamics, and use of learning resources. At the same time, no single indicator gives enough grounds for a clear conclusion. For example, low activity in an LMS can be connected with low engagement, technical difficulties, or working with materials outside the platform.

Digital feedback can perform informational, corrective, predictive, recommendation, reflective, and managerial functions. Informational feedback reports a result or a state of task completion. Corrective feedback explains an error and how to fix it. Predictive feedback warns about a possible risk. Recommendation feedback suggests the next learning action. Reflective feedback supports the learner's evaluation of their own progress. Managerial feedback provides the teacher with information for decision-making.

Based on the systematization, a matrix was developed (Table 1). It connects an analytical indicator, its possible pedagogical interpretation, a form of digital feedback, and a managerial and pedagogical decision.

Таблиця 1.

Matrix for using learning analytics and digital feedback in educational process management

Analytical indicator	Possible pedagogical interpretation	Digital feedback	Managerial and pedagogical decision
Low current assessment results	Insufficient understanding of the topic, misunderstanding of requirements, or ineffective task strategy	Explanation of typical mistakes and a link to relevant material	Consultation, repeated explanation, and differentiated task
Repeated similar mistakes	Unstable understanding of a concept or incorrect way of action	Corrective comment explaining the reason for the mistake	Training task, repeated study of the material
Sharp decrease in results	Temporary difficulties, overload, or loss of motivation	Personal message with a proposal to clarify the reasons	Individual conversation, adjustment of workload
Stable high results	Confident understanding of the material, readiness for more complex tasks	Message about progress and recommendations for deeper work	Higher-level task, research work
Low frequency of LMS logins	Low engagement, technical difficulties, or use of other sources	Neutral message asking about possible reasons	Checking access to alternative formats of materials
Frequent logins with low results	High effort without proper results or an ineffective learning strategy	Recommendation about the order of work	Consultation, roadmap for studying the course
Late submission of tasks	Difficulties with self-organization or overload	Reminder with deadline and next steps	Intermediate deadlines, individual schedule
Accumulation of unfinished tasks	High risk of academic failure	Warning to the learner and signal to the teacher	Plan for completing missed tasks, personal consultation

Uneven activity during the course	Delayed task completion or poor time planning	Visualization of activity and recommendations for regular work	Division of tasks into stages, intermediate control
Low participation in discussions	Communication difficulties, low motivation, or an unsuitable interaction format	Personal invitation or alternative form of response	Work in a smaller group, asynchronous participation
Low contribution to a group task	Passive position or unclear distribution of roles	Request for self-assessment of own participation	Redistribution of roles, clarification of responsibility
Mismatch between self-assessment and result	Insufficient ability to evaluate the quality of one's own work	Comparison of self-assessment with criteria	Work with a rubric, peer assessment
Non-use of recommended resources	Lack of information or low perceived usefulness	Explanation of the purpose of the resource	Reduction or restructuring of materials
Repeated test attempts without improvement	Guessing answers or not understanding mistakes	Explanation of mistakes and recommendation to return to the material	Changing the task bank, consultation
No reaction to feedback	Recommendation is not understood or cannot be used	Repeated message in a simpler form	Change of feedback format, discussion of recommendations
Improvement after recommendations	Effectiveness of the selected support	Message about positive dynamics	Continuation of the selected approach
No improvement after several interventions	The selected form of support is not suitable	Signal to the teacher and invitation to discussion	Review of the intervention, additional support

The matrix is indicative and does not establish an automatic connection between an indicator and the cause of a learning problem. Before making a decision, it is necessary to check other data, compare the indicator with previous results, and, if needed, contact the learner. The proposed approach also helps to separate automated and non-automated actions. A system can detect a deviation, create a visualization, or send a standard message. However, the interpretation of causes, the choice of support, and the evaluation of consequences remain the professional responsibility of the teacher. The practical value of the matrix is that it does not require complex predictive algorithms. Most indicators are available in standard LMS reports, electronic gradebooks, and testing systems. This makes it possible to use learning analytics to support pedagogical decisions, even with limited technical resources.

Discussion. The results confirm that learning analytics has pedagogical value only when it is connected with feedback and concrete teacher decisions. Digital indicators, even if accurate, do not improve the educational process on their own. They must be interpreted with regard to the task type, progress dynamics, learning organization, and possible external circumstances.

The proposed matrix corresponds to the modern understanding of learning analytics as a support tool, not as a tool for automating pedagogical decisions. Its advantage is that it connects four components that are often studied separately: an analytical indicator, a possible interpretation, a form of digital feedback, and a managerial and pedagogical action. Such a structure helps avoid a situation in which a teacher receives a large amount of data but lacks a clear way to use it.

At the same time, the matrix is indicative. The same indicator cannot be directly linked to one specific reason or decision. For example, low activity in a learning management system may show low engagement, technical problems, or work with materials outside the platform. Therefore, the use of the matrix requires additional data checks and the teacher's professional judgment.

The practical value of the proposed approach lies in its ability to be used without complex predictive systems. Basic indicators of activity, achievement, deadlines, and repeated mistakes are available in most modern LMSs. This makes it possible to move gradually from simple recording to analytically grounded feedback, even when technical resources are limited.

The limitation of the study is connected with its theoretical and analytical character. The matrix has not been empirically tested. Therefore, its use requires further testing in different subjects and learning formats. A promising direction is to study which combinations of analytical indicators and feedback forms have the strongest effect on learning activity, self-regulation, and learner outcomes.

Conclusions. Learning analytics and digital feedback are connected components of educational process management. Analytical data receive pedagogical meaning only when they are properly interpreted and used to support further actions of the learner and the teacher.

The study systematized the main indicators of learning activity and defined informational, corrective, predictive, recommendation, reflective, and managerial functions of digital feedback. The developed matrix connects an analytical indicator, its possible pedagogical interpretation, a message form, and a relevant managerial and pedagogical decision.

The matrix is indicative because digital traces do not give enough grounds to identify the causes of learning behavior with certainty. Its use requires checking the data, considering the educational situation, and relying on the teacher's professional judgment. Further research should focus on empirical testing of the matrix and on determining the effectiveness of specific types of digital feedback.

Use of artificial intelligence (AI) tools. During manuscript preparation, AI (Grammarly) was used as an auxiliary tool for the technical review of selected author-written text at the levels of grammar, spelling, and punctuation. The AI tool was not used to generate the substantive parts of the article, including the aim, methodology, results, discussion, conclusions, or references. All language corrections suggested by the AI tool were verified by comparing them with the original text and by checking terminology, content accuracy, and consistency with the cited sources. The use of AI did not affect the research results, their interpretation, or the conclusions.

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