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Using educational analytics for adaptive management of academic processes in universities

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Abstract

Digital transformations in higher education have highlighted the need for further use of educational analytics as a separate mechanism to support adaptive management of academic processes. The purpose of the proposed article is to analyze the patterns in the application of analytical data to improve the effectiveness of management decisions in universities (using the example of Ukraine). The study was carried out within the framework of a mixed design, which combined quantitative data analysis of more than 15,000 students and semi-structured interviews (25 participants from among teachers and administrators). The proposed results demonstrate the existence of a steady growth in the digital activity of students (up to +59% in three years) and close links between behavioral and academic transformations ($r = 0.55$–0.71). The regression model made it possible to establish that separate, integrated analytical panels, regular reporting, and early warning systems have become the main factors for increasing the adaptability of management in modern universities. Qualitative analysis showed an increase in managerial reflexivity, ethical awareness, and staff readiness to further use analytics. The conclusions indicate that educational analytics has now become an effective mechanism for universities to transition to an adaptive model of effective management of educational processes.

Keywords: Adaptive management, Educational analytics, Ethical culture, Digital transformation, Higher education, Professional development.

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Contents

Contribution of this paper to the literature
The study expanded the researchers' understanding of educational analytics not only as a technical tool but as an independent management mechanism that ensured the transition of higher education institutions to adaptive models of educational process management.

1. Introduction

Recently, higher education institutions have adopted approaches based on digital data. This has significantly improved the quality, efficiency, and personalization of educational trajectories. The concept of learning analytics that is, the process of collecting, researching, classifying, analyzing, and interpreting information about the academic environment and students' behavior has opened new perspectives for further understanding of learning mechanisms and for making informed decisions in educational management (Artemchuk, Marukhlenko, Sokrovolska, Mazur, & Riznyk, 2024). Besides, the active use of various analytical tools has influenced the fact that university administrations have gained the ability to track student engagement, predict the risks of their potential academic failure, and optimize educational trajectories. However, despite the large number of relevant studies in this area, many scientific and practical gaps exist. Modern researchers primarily focus on the technical and predictive aspects of educational analytics, such as the effectiveness of dashboards or the use of algorithms in machine learning (Mutimukwe, Viberg, Oberg, & Cerratto-Pargman, 2022).

Besides, there is insufficient research on the extent to which the results of analytical monitoring can be used in the future in adaptive management of educational processes: in the process of making operational decisions, improving curricula, allocating resources, and developing strategies to support students. It is also important to pay attention to the ethical issues in the process of using digital data, the potential readiness of teaching staff, and the organizational culture of higher education institutions (Hernández-de-Menéndez, Morales-Menendez, Escobar, & Ramírez Mendoza, 2022).

Overcoming these gaps is quite crucial for realizing the potential of educational analytics, understanding it as the basis for forming tools for the development of universities of the future. The transition from data collection to its targeted use will allow for improving adaptive management, contributing to increasing the flexibility, evidence, and effectiveness of educational systems. The purpose of the proposed article is to explore the possibilities of using educational analytics for adaptive management of educational processes in higher education institutions, identify potential obstacles to their integration, and focus on effective models of their implementation. Accordingly, the research questions are as follows:

1. How have the intensity and patterns of students' digital activity in learning management systems changed over the period 2022/23–2024/25 in Ukrainian universities?
2. What is the relationship between students' behavioral digital indicators and academic outcomes?
3. How does the implementation of educational analytics infrastructure influence the adaptability, efficiency, and quality of management decision-making?

2. Literature Review

2.1. Educational Analytics and Monitoring Infrastructure

Learning analytics has become one of the standard tools for monitoring a holistic learning management system. Previous studies focused on the formation of work cycle models, problems of visualization of student involvement in educational processes (Guzmán-Valenzuela, Gómez-González, Rojas-Murphy, & Lorca-Vyhmeister, 2021). Later, scientists emphasized the integration of analytics, learning management systems and university databases, which became the basis for long-term analytical observations (Cerratto Pargman & McGrath, 2021). The COVID-19 pandemic and the related quarantine restrictions led to the fact that analytics began to be considered as a tool for adaptive management (Gašević, Tsai, & Drachsler, 2022; Rosa et al., 2022). Recent researchers usually do not doubt that educational analytics is an important part of the institutional strategy in ensuring the quality of education (De Silva et al., 2022; Śliwa, Saienko, & Kowalski, 2021).

Modern researchers have distinguished behavioral, academic, and institutional indicators of learning (Heikkinen, Saqr, Malmberg, & Tedre, 2023). If during the 2010s, elementary activity data (the number of entries into the educational system, viewing materials, and downloading completed tasks) were available for analysis, today the situation is different. Recent studies have demonstrated the effectiveness of composite indicators: engagement indices, risk maps, subject load indicators, etc. (Awan, Afshan, & Memon, 2021; Márquez, Henríquez, Chevreux, Scheihing, & Guerra, 2024). The evolution of international standards in data exchange processes (xAPI, Caliper) has made it possible to ensure compatibility between different systems. In turn, this has created the basis for making decisions in real time.

2.2. Risk Forecasting and the use of AI

Many studies are devoted to the formation of new models for predicting academic risks (Beerkens, 2022; Cabı & Türkoğlu, 2025). The use of neural network approaches (the use of artificial intelligence) against this background looks like a new vector of research. However, it is also the most promising, given the further integration of AI into analytical and search systems (Cisel, 2023). Some studies have proposed using separate risk thresholds to avoid wrong decisions when working with automated systems (Molla-Esparza, Gómez-Núñez, & García-García, 2025).

Researchers note the importance of creating dashboard systems as a component of management (Rets, Herodotou, & Gillespie, 2023). These tools allow teachers and administrators to quickly receive information about the course of the educational process. Accordingly, mechanisms for correction, automatic prompts, etc., function, which also act as the core of adaptive management of the educational process (Mazur, Bolhov, Akhnovska, Dluhopolskyi, & Kozlovskyi, 2025; Timofte, 2022). Personalization of the educational process in such circumstances will emphasize the connection between analytics and the development of self-regulated learning.

2.3. Ethical, Legal, and Organizational Dimensions of the use of Educational Analytics

Modern research also focuses on the issue of ethical interaction (Mavroudi, 2023). Data confidentiality and transparency in their use are important for the further use of the principles of informed consent, data minimization, and understanding of key algorithms, etc. A separate direction is the functioning of ethics committees for conducting educational analytics, the use of automated systems for assessing the adequacy of analytical solutions (Dahal, Nugroho, Schmidt, & Sänger, 2025). Accordingly, the further application of educational analytics in university management should correspond to the development of the analytical culture of teachers (Lim & Kenayathulla, 2024; Quadri & Shukor, 2021). The introduction of appropriate professional development programs in such circumstances is an important task for the university community.

In general, trends in understanding modern scientific literature on the use of educational analysis in managing educational processes can be summarized as follows (See Figure 1).

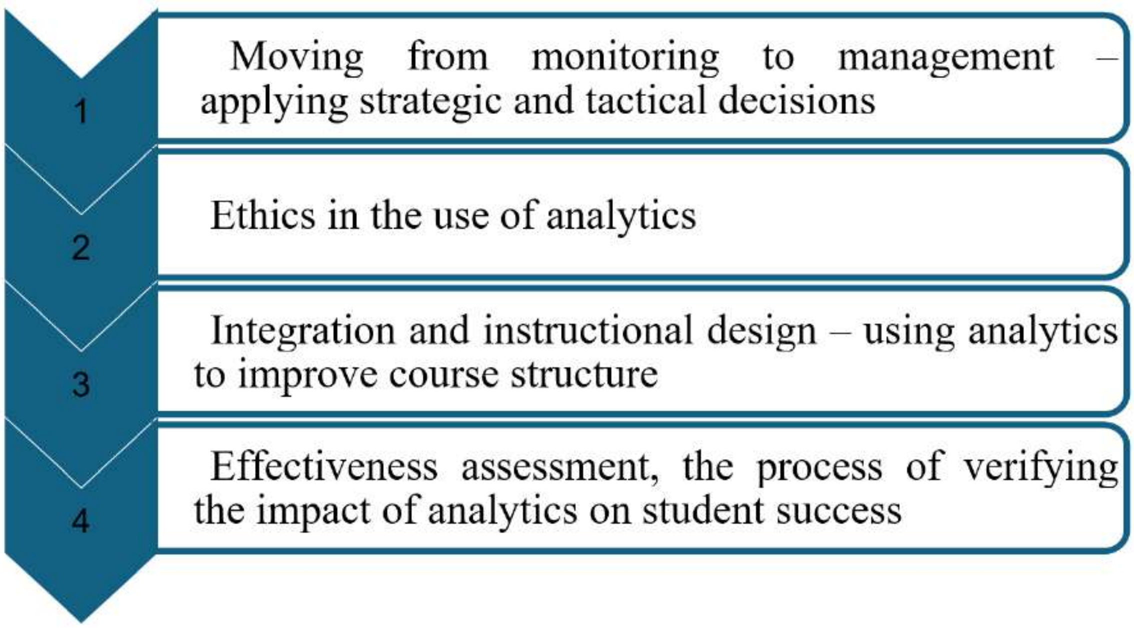

Figure 1. Current trends in scientific research.

Despite the significant scientific interest in this issue, there are some gaps. First, the issues of external validity of models, the balance between personal information and the right to access it, the features of privacy and the benefits of data, the economic feasibility of using digital analytical systems remain open. Further research should be aimed at the application of analytical approaches and pedagogical design, and the creation of sustainable mechanisms in adaptive management of higher education institutions.

Thus, as can be seen from the analysis, most of the existing works were based on data from a single institution or short-term observations. This study expanded the empirical basis by using large-scale, multi-year data from several universities. The novelty of the work also consisted in the empirical identification of specific management factors (integrated analytical panels, regular reporting, etc.) that statistically influenced the adaptability of management. In addition, unlike technocratic approaches, the study integrated the ethical and organizational dimensions of the use of educational analytics.

3. Methodology

3.1. Research Design

The study used both quantitative and qualitative methods. Based on the concept of adaptive management of educational processes, an analysis of educational analytics data in higher education institutions was performed. The goal was to determine the patterns of application of analytical data to support management decisions in universities, assess the potential for further use of analytics in the strategic planning system.

The methodological basis of the work is the concept of adaptive management of educational processes, according to which management decisions in universities are adjusted based on continuous analysis of educational and behavioral data. Unlike most previous studies, which mainly analyzed individual student learning outcomes, this study considers analytics as an institutional management mechanism.

The study was organized into three stages. During the implementation of the review and analytical stage, the systematization of scientific literature, individual constituent universities, general provisions and strategies for the digitalization of education (2018–2025) was carried out. During the implementation of the quantitative stage, the use of indicators of the effectiveness of educational processes in a sample of universities was envisaged. The qualitative stage involved the analysis of the results of interviews and focus groups with representatives of the administration and teachers of higher education institutions.

3.2. Sample and Data Collection

The sample consisted of 10 higher education institutions (public and private, of various profiles, from the Central and Western regions of Ukraine) with developed electronic educational environments (Moodle, Canvas, OpenEdX). The quantitative analysis included anonymized data from about 15,000 students. Data were collected from digital activity logs of over 15,000 students across the last three full academic years (2022/23–2024/25). The sources of processed data were LMS activity logs (logins, viewing educational materials, etc.), academic indicators (average score, progression), and data from student services (applications for consultations, participation in mentoring programs).

Besides, to check the stability of the results obtained, a basic sensitivity analysis was conducted. In particular, the stability of regression coefficients in subsamples by year and by type of university (public/private) was assessed. Additionally, the impact of potential confounders (group size, specialty, form of study) was tested by including them in the control models. The robustness of the effects was confirmed by the closeness of the parameters in the time splits and the insignificant variation of the standard errors ($\Delta\beta < 0.05$).

For the further organization of the qualitative stage, 25 semi-structured interviews were organized with managers, heads of IT departments, and teachers persons responsible for monitoring the educational process with an average duration of 45 minutes.

3.3. Data Analysis

Descriptive statistics, correlation analysis (Pearson's r), and multivariate regression were used for quantitative analysis. This generally allowed us to assess the relationship between engagement, success, and management interventions. The effect of learning analytics and its impact on management quality was tested using ANCOVA, controlling for background variables such as group size and specialty.

Qualitative interview data were analyzed according to the scientific method of thematic analysis in NVivo 14. In particular, the dominant categories identified were institutional readiness, ethical aspects, changing teacher roles, and effects on students. Additionally, quantitative data were extracted from institutional learning management systems (Moodle, Canvas, OpenEdX) using standardized ETL (Extract–Transform–Load) procedures. Anonymized tables of user activity (number of logins, course views, assignment submissions, feedback timestamps) and academic indicators (grade point average, performance dynamics, course completion) were used for extraction.

Before analysis, data was cleaned and merged using Python scripts and SQL queries. Missing values were handled by multiple imputations for continuous variables and modal value replacement for categorical variables. Outliers and anomalies were eliminated by winsorization at the 5th and 95th percentile levels. Duplicate records were identified by unique student identifiers and removed. Timestamps were synchronized by converting all LMS data to UTC+2 (Kyiv) and aligning with the academic calendar (beginning of the semester, examination sessions).

Operationalization of indicators:

Engagement Index (EI) – a composite indicator calculated as the standardized sum of the frequency of logins, viewings of educational resources and interactions in forums (z-scores, normalized on a scale of 0–100).

Academic Growth Index (AGI) – the ratio of the current semester grade point average (GPA_t) to the previous one (GPA_t-1), standardized by the average value of the corresponding program (AGI = GPA_t / GPA_t-1).

Risk level – the probability of expulsion, calculated using logistic regression considering the variables of engagement and learning outcomes (risk > 0.6 was interpreted as high).

Timeliness is the average delay (in days) between the deadline and the actual submission of the assignment; negative values indicate early submission.

Besides, Quantitative analysis was conducted using descriptive statistics, Pearson's correlation coefficient (r) and multiple regression in SPSS 29. At the same time, the impact of using learning analytics on the quality of management decisions was tested using ANCOVA with control for background variables (group size, specialization and baseline GPA). The reliability of the composite scales was confirmed based on Cronbach's $\alpha = 0.86$.

Qualitative data from 25 semi-structured interviews were transcribed verbatim and analyzed using thematic analysis. Based on the coding process, we identified four dominant themes: institutional readiness, ethical and private aspects, transformation of teacher roles, and impact on students. The validity of the results was ensured through triangulation of sources, including comparison of interview data and statistical indicators.

3.4. Reliability

To check the reliability of quantitative instruments, Cronbach's $\alpha = 0.86$ was calculated. This indicator indicated high internal consistency of the scales. The validity of the qualitative analysis was ensured based on data triangulation (comparison of interview results, documents, and statistics). All data obtained were anonymized. The study was conducted in accordance with the ethical norms of the GDPR and the internal rules of the universities regarding the processing of personal data. All participants in the study provided informed consent to participate.

This study was reviewed and approved by the Department of Professional and Pedagogical, Special Education, Andragogy, and Management of the Educational and Research Institute of Pedagogics at Zhytomyr Ivan Franko State University (Minutes No. 1, January 15, 2022).

4. Results

An analysis of the digital activity logs of over 15,000 students revealed an increase in the volume of learning data over the three academic years (2022/23–2024/25). The average number of entries per student increased from 218 to 347 per semester, a 59% rise. Notable changes included logins (+44%), viewing learning resources (+53%), participation in forums (+38%), and timeliness of assignment submissions (+27%). These trends indicate an increase in digital interaction between students and teachers, as well as a transition by universities to constant monitoring of educational processes in real time (See Table 1).

Table 1. Changes in student digital activity (2022/23 – 2024/25).

Indicator	2022/23	2023/24	2024/25	Growing, %
Average number of logins per student	52	66	75	+44 %
Views of educational resources	87	113	133	+53 %
Participation in forums	32	38	44	+38 %
Timeliness of assignment submission (%)	64	70	81	+27 %
Average number of entries per student	218	276	347	+59 %

Thus, the changes identified were significant, as the growth in digital activity exceeded 25% across all key indicators. In addition, the total growth in data volume (+59%) indicated a sustained structural transformation of educational interaction.

Additionally, correlation analysis ($p < 0.01$) revealed strong relationships between behavioral and academic indicators (See Table 2). The correlation coefficients ($r = 0.55–0.71$) indicated medium to large effects according to Cohen's criteria. This indicated that the effect had substantial practical power. The negative correlation between the frequency of consultations with consultants and the risk of dismissal ($r = –0.36$) was consistent with a medium-strength effect and confirmed the preventive effect of early management interventions.

Table 2. Correlations between behavioral and academic indicators.

Behavioral indicator	Academic performance	r (Pearson)	Significance (p)
LMS activity	Overall performance	0.62	< 0.01
Forum participation	Self-regulation	0.55	< 0.01
Timely assignment submission	Progression/Course completion	0.71	< 0.001
Consultation requests	Risk of expulsion	–0.36	< 0.01

Activity in the learning management system ($r = 0.62$) is positively correlated with overall academic performance. In turn, participation in forums ($r = 0.55$) has a positive relationship with the level of student self-regulation. At the same time, timely submission of assignments ($r = 0.71$) is positively correlated with progression in learning, the rate of course completion. The study also found a negative relationship ($r = –0.36$). It is established between the level of risk of expulsion and the frequency of contacts with academic consultants. This indicates the preventive effect of timely interventions (Tsekhmister, 2024).

The constructed multivariate regression model ($R^2 = 0.68$; $p < 0.001$) demonstrated that three variables have the greatest impact on the level of management adaptability (AGI): the presence of integrated analytical panels ($\beta = 0.41$), regularity of reporting to deans ($\beta = 0.29$), and automated early warning systems ($\beta = 0.24$). Variables such as group size and form of training were found to be statistically insignificant, which confirms the universality of the model for different contexts. Besides, comparative analysis (ANCOVA) between universities that implemented educational analytics panels and those where they were not used showed an average difference in the adaptability index of +0.37 SD (95% CI [0.24; 0.49]), which corresponds to an effect of medium strength (See Table 3).

Table 3. Factors influencing management adaptability.

Predictor	β- coefficient	Significance (p)	Interpretation
Integrated analytical panels	0.41	< 0.001	The greatest impact
Regular reporting for dean's offices	0.29	< 0.01	Factor of stability in management
Automated early warning systems	0.24	< 0.05	Impact on operational decisions
Group size	0.07	n/d	Negative impact
Form of training	0.05	n/d	Negative impact
$R^2 = 0.68$; $p < 0.001$			

The impact of learning analytics on academic outcomes was evident in the increase in student grade point average (GPA) from 78.4 ± 8.9 to 82.6 ± 7.5 points ($t = 6.12$; $p < 0.001$) after the implementation of analytics systems in the 2022/23 academic year. The rate of early withdrawal decreased from 14.8% to 9.6%, and the proportion of students using individual adaptive trajectories increased to 42%. In addition, an increase in the frequency of LMS logins by 25% was recorded, especially in groups where teachers used automated notifications about learning progress. The value of the coefficient of determination ($R^2 = 0.68$) indicated that the model explained 68% of the variance in management adaptability. This was generally consistent with a large effect for social and management research. The high value of the t-test together with $p < 0.001$, indicated a significant and stable difference between the indicators before and after the implementation of analytics.

Qualitative analysis of the results of 25 semi-structured interviews with teachers and administrators confirmed the quantitative findings and provided a deeper understanding of the processes behind them. Three key themes were identified: Data-Driven Reflexivity, Adaptive Decision-Making, and Ethical Awareness and Trust (See Table 4).

Table 4. Interview themes, frequency of mentions, and analytical interpretation.

Topic	Frequency of mentions (%)	Typical quotes/Examples	Analytical interpretation
Data-driven reflexivity	38 %	"We used to see results at the end of the semester; now we see results in the second week."	Data is used to self-correct teaching.
Adaptive decision-making	34 %	"Weekly reports allow us to quickly adjust schedules and mentoring programs."	Data supports operational management.
Ethical awareness and trust	28 %	"We have created our own code of ethics for data use."	Ethical culture of using analytics is formed.

Faculty members noted that dashboards have become an important tool for self-evaluation of courses and correction of teaching methods: about 70% of respondents use data to change the assessment structure or pace of learning. One coordinator noted: "Previously, we only saw results at the end of the semester; now we get signals as early as the second week."

Administrative staff emphasized that weekly analytical reports help make flexible decisions at the micro level – from reallocating mentors to updating academic support policies. At several universities, after implementing dashboards, the number of student complaints decreased by an average of 18%. At the same time, 84% of respondents indicated concerns about the transparency of algorithms and the confidentiality of student data. This stimulated the creation of special codes of ethics for the use of analytics in some institutions, which became a side but valuable effect of digitalization (Gumenyuk, Kushnarov, Bondar, Haludzina-Horobets, & Horban, 2021).

Respondents named several important factors among the main barriers to implementation (See Figure 2).

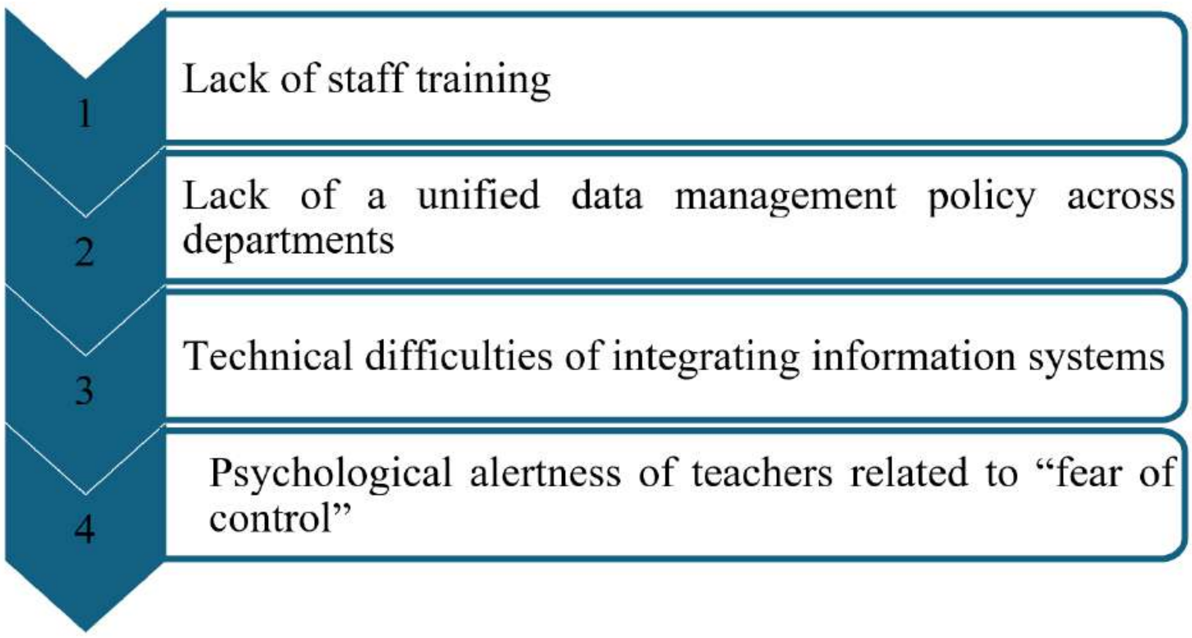

Figure 2. Barriers to using digital analytics.

Despite this, most respondents (76%) recognized that analytical tools really improve the quality of education and contribute to more informed management decisions. The implementation of learning analytics not only improved academic outcomes but also produced measurable management effects. The average time for intervention (from detection of academic risk to administrative action) decreased from 18 to 7 days, reducing the response cycle by 61%. Universities reported that early identification of at-risk students saved approximately 120–150 staff hours per semester previously spent on manual monitoring. At the same time, the use of automated dashboards reduced the need for routine reporting and allowed faculty to reallocate up to 12% of their time to mentoring and personalized feedback. In two pilot institutions, the use of predictive analytics allowed scholarship resources to be reallocated to proactively support students. This, in turn, led to a 9% reduction in unnecessary financial aid adjustments. In this way, analytics directly impact management efficiency, resource optimization, and the overall efficiency of education management systems (Yuryk, Holomb, Konovalova, Vivsyannuk, & Tsekhmister, 2023). Overall, the data indicated that educational analytics is an important and powerful tool for developing adaptive management in higher education. It increases the effectiveness of educational processes and creates a new culture of decision-making based on data, ethics, and participation of all participants in the educational environment.

5. Discussion

In addition, the results indicated that the use of educational analytics in higher education institutions in Ukraine has moved from experimental practice to a systemic management strategy. In particular, the study revealed an increase in the volume of digital data. This generally corresponds to global trends in the transition of universities to a data-driven management model, in which information becomes a key resource for making management decisions. An increase in the frequency of logging into the system, reviewing resources, and timely completion of tasks indicated the existence of an increase in the digital maturity of students and teachers, as well as the transformation of the educational environment towards analytical processes (Bondar, Shestopalova, Hamaniuk, & Tursky, 2023; Stender, Bulkot, Iastremska, Saienko, & Pereguda, 2024).

The increase in academic success and a decrease in the rate of withdrawals after the implementation of analytical systems confirmed the thesis about the effectiveness of analytics as a tool for adaptive management. This conclusion can be compared with international studies that indicated that the use of analytics allows for timely identification of risks and interventions aimed at supporting students (Artyukhov, Simakhova, Artyukhova, Bojaruniec, & Wit, 2023; Lokhman, Serebrenikov, Beridze, Cherep, & Dashko, 2020; Pasichnyi, Serhieiev, Shevchenko, Petrukha, & Hryvnak, 2024). High correlation coefficients between behavioral and academic variables ($r = 0.55$–0.71) indicated the existence of a connection between digital activity and academic results, which confirms the validity of approaches to analyzing the "digital footprint" of students (Nykyporets, Stepanova, & Hadaichuk, 2023).

An increase in the average GPA by more than 4 points and a decrease in the rate of early withdrawals by 5.2% indicated the practical effect of the implementation of individualized educational trajectories and early warning systems. This can be reconciled with previous findings by other researchers who indicated the positive impact of personalized recommendations on student motivation and self-regulation (Taylor, Yeung, & Bashet, 2021; Vasylyk, Melnyk, Prytuliak, & Chervinska, 2024). Thus, the implementation of NA improves academic performance and fosters a responsible, conscious attitude of students toward their own learning. The regression model showed that the strongest predictors of adaptability are the presence of integrated analytical panels, regular reporting, and early warning systems. These data indicated that the institutional structure of governance is crucial for realizing the potential of analytics. Therefore, the use of data in governance is critically important. Researchers also highlighted the following findings (Abouelenein, Selim, & Aldosemani, 2025; Ngulube & Ncube, 2025).

Besides, Qualitative results confirm this conclusion: in those universities where analytical reports have become a regular part of the governance cycle, a new governance culture based on evidence has been formed. Respondents' statements indicated that data is beginning to play the role of a controlling and reflective mechanism. This has made it possible to rethink educational practices and adjust pedagogical approaches in real time (Bilytska, Andriiashyk, Tsekhmister, Pavlenko, & Savka, 2022; Bobro, Bielikov, Matveyeva, Salamakha, & Kharchun, 2025).

At the same time, it is worth paying attention to the high proportion of mentions of ethical issues – 84% of respondents expressed concern about data confidentiality. Thus, there is an awareness that the effectiveness of analytical systems directly depends on trust in them. As researchers note, ethical awareness of users is not only a condition for compliance with legislation (GDPR), but also an important component of the institutional sustainability of the implementation of analytics (Guseva et al., 2022; Honson, Vu, Tran, & Tejada Estay, 2024; Weidlich et al., 2025).

Universities that have established internal codes of ethics for data use demonstrate higher integration of analytics systems, less staff resistance, and greater student openness to using analytics tools. This supports the thesis that ethical infrastructure is becoming no less important than technical or managerial (Dixon, Howe, & Richter, 2025; Manganello & Fante, 2025).

Despite the positive results, several barriers have been identified: insufficient training of staff in interpreting analytical data, technical difficulties in integrating different sources, and psychological wariness of teachers due to "fear of control". These barriers are typical of the stage of formation of an analytical culture in higher education (Mejeh & Rehm, 2024). They indicate the need for professional development of teachers, aimed not only at digital competencies, but also at the formation of analytical thinking, the ability to see data as a resource for improvement, not just for control (Borchers & Pardos, 2025; Viberg et al., 2024).

A comparison of quantitative and qualitative data demonstrates that educational analytics plays a dual role: on the one hand, as a technological monitoring tool, and on the other, as a catalyst for a management culture based on reflection, transparency, and accountability.

Institutions that have developed quality formalized data policies have shown high adaptability indicators (AGI > 0.7). However, fragmented initiatives have had a short-term effect. This has confirmed the thesis that the sustainability of analytical practices depends on their systematic implementation (Bondar, Humenchuk, Horban, Honchar, & Koshelieva, 2021; Lim et al., 2021; Munguia, Brennan, Taylor, & Lee, 2020). Further research should be aimed at quantitatively assessing the impact of educational analytics on the quality of management decisions and student educational outcomes in the long term. In addition, it is worth paying attention to the qualitative development of models of ethical and fair use of AI in analytical systems.

The proposed results indicated that the development of educational analytics in universities has become an important technological shift. At the same time, it is also indicated that there is a shift in the understanding of educational effectiveness. The traditional management model based on periodic reporting has given way to digital processes. This is confirmed by the results of other researchers (Hilliger et al., 2020; Whitelock-Wainwright, Tsai, Drachsler, Scheffel, & Gašević, 2021). Although other scholars have also pointed to the importance of engagement, academic progress, and risk indicators (Fernsel, Kalff, & Simbeck, 2024), this means that universities have moved from retrospective to predictive management, in which data captures the state and predicts future trends.

6. Conclusions

Hence, the use of learning analytics systems in higher education institutions has become a tangible mechanism for increasing the effectiveness of adaptive management of educational processes. Analysis of the obtained empirical data demonstrated a steady increase in the level of interaction with learning platforms, reflecting increased digital participation of education seekers and some transformations in managerial approaches to the functioning of higher education institutions.

The results obtained also demonstrated that behavioral activity indicators are closely related to academic achievements. In addition, integrated analytical panels, regular reporting, and early warning systems have become key predictors of the successful implementation of adaptive management. The effects of implementation are manifested in an increase in the average GPA, a decrease in the rate of withdrawals, and an increase in the use of individual educational trajectories.

Qualitative analysis showed that the culture of decision-making in universities has changed, stimulating the development of reflexivity, operational responsiveness, and ethical awareness. At the same time, barriers remain—uneven staff training and incomplete data management policies.

Therefore, educational analytics has become an institutional tool for strategic management, enabling universities to shift from a reactive to an adaptive development model focused on personalization, transparency, and evidence. Further development requires strengthening the ethical framework, increasing staff's analytical competence, and creating sustainable policies in higher education.

6.1. Limitations

The research methodology has certain limitations that need to be paid attention to during the subsequent interpretation of the results. Given the Ukrainian context, the study covered Ukrainian higher education institutions, which rather indicates the locality of the empirical data obtained, which may in the future become part of a larger and more global study. It is also worth considering that the sample of 25 people for structured interviews is quite limited, so it will require further scaling. This will allow confirming or correcting the results obtained. In addition, it is worth considering that the study was quasi-experimental in nature. Thus, the work does not make definitive cause-and-effect conclusions regarding the impact of educational analytics on management decisions and academic outcomes. Future articles should use experimental or longitudinal designs. It will also be important to consider controlled implementation of analytical tools in different institutional settings.

A separate limitation is that the study did not include an economic assessment of the effectiveness of implementing educational analytics (cost–benefit analysis). A promising direction for future research will be analyzing the cost-benefit ratio and resource allocation in higher education institutions.

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