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Data-Driven Risk Management in Universities: Application of Analytics and Predictive Models

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Abstract

Modern universities operate in an environment of increasing uncertainty caused by digital transformation, financial instability, demographic change, competition for students and academic staff, cybersecurity threats, and rising expectations from regulators and society. Traditional risk management in higher education often remains fragmented, reactive, and insufficiently connected with strategic decision-making. The purpose of this study is to develop a conceptual and applied framework for data-driven risk management in universities through the integration of enterprise risk management, key risk indicators, dashboards, learning analytics, and predictive models. The study is conceptual-applied in nature and is based on a review of international literature on enterprise risk management, learning analytics, early warning systems, predictive analytics, and digital governance in higher education. The methodology includes system analysis, comparative analysis, risk mapping, maturity assessment, and conceptual modelling. The results propose an integrated data-driven ERM framework consisting of five components: risk data architecture, risk taxonomy, key risk indicators, predictive models, and governance response mechanisms. The study also presents illustrative risk indicators, risk thresholds, a risk scoring matrix, and examples of predictive model application for academic, financial, digital, human resource, operational, and reputational risks. The findings show that analytics and predictive models can transform university risk management from a formal control function into a proactive, measurable, and evidence-based governance system. The practical significance of the study lies in the possibility of applying the proposed framework in higher education institutions, including universities in Kazakhstan, to improve risk identification, early warning, strategic planning, and institutional resilience.

Keywords: Data-driven risk management, Universities, Predictive models, Learning analytics, Enterprise risk management.

Introduction

Universities are increasingly exposed to a complex combination of strategic, financial, academic, digital, reputational, operational, and human resource risks. These risks are no longer isolated events; they are interconnected signals of institutional vulnerability. For example, a decline in student engagement may begin as an academic risk, later lead to financial losses through dropout, and eventually create reputational consequences. Similarly, weak cybersecurity may initially appear as an operational risk but can quickly affect trust, legal compliance, and institutional continuity.

In the context of higher education transformation, risk management can no longer be limited to formal reporting, internal audit, or post-factum control. The university of the twenty-first century requires a proactive and integrated system that identifies weak signals before they become institutional crises. This is especially relevant for universities moving toward the model of University 4.0, where education, research, digital platforms, entrepreneurship, industry cooperation, and data ecosystems become interconnected.

The academic literature shows that learning analytics and predictive analytics have become important instruments for supporting student success, identifying at-risk students, and improving institutional decision-making. Siemens emphasizes that learning analytics has emerged as a discipline focused on using educational data to understand and optimize learning processes (Siemens, 2013). Cui et al. review predictive models of student success in higher education and show that universities increasingly use institutional data to identify

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students who may be at risk of failure or withdrawal (Cui et al., 2019). Bañeres et al. demonstrate that early warning systems can detect at-risk students in online higher education and support timely intervention (3) (Bañeres et al., 2020). Later research further confirms the value of early warning systems in identifying and supporting online dropout learners (Bañeres et al., 2023).

At the same time, the literature on artificial intelligence and digital analytics in higher education shows that universities increasingly apply machine learning, data mining, and predictive tools in learning environments. Zawacki-Richter et al. identify the growing application of artificial intelligence in higher education but also highlight the need for stronger involvement of educators and institutional decision-makers in the design and use of such systems (Zawacki-Richter et al., 2019). De Oliveira et al. show that learning analytics can contribute to dropout prevention, but they also stress the importance of practical implementation and institutional integration (de Oliveira et al., 2021).

However, most studies on learning analytics focus mainly on academic performance, student retention, or dropout prevention. At the same time, research on enterprise risk management in higher education often focuses on governance structures, internal control, risk registers, and institutional accountability. Khaw and Teoh show that risk management in higher education has been developing as a research field, but still requires stronger integration between risk governance, measurement tools, and institutional performance (Khaw & Teoh, 2023). This creates an important research gap: the connection between enterprise risk management and data-driven predictive analytics remains insufficiently developed.

This study argues that universities should move from traditional ERM to data-driven ERM. In this approach, risks are not only identified and described in a risk register but are also measured through key risk indicators, monitored through dashboards, and forecasted through predictive models. The novelty of the study lies in developing a conceptual and applied framework that combines enterprise risk management, learning analytics, predictive modelling, and university governance into one integrated system.

The purpose of this study is to develop a data-driven risk management framework for universities based on analytics, key risk indicators, dashboards, and predictive models.

The study addresses the following research questions:

1. How can universities integrate analytics and predictive models into enterprise risk management?
2. Which types of university risks can be monitored through data-driven indicators?
3. What conceptual framework can support proactive and evidence-based risk governance in higher education?

The hypothesis of the study is that the integration of data analytics, predictive models, and ERM instruments can improve the timeliness, accuracy, and strategic relevance of university risk management.

Materials and Methods

This study is conceptual-applied in nature. It does not claim to test a full empirical predictive model on primary institutional data. Instead, it develops a research-based framework for future empirical testing and practical implementation in universities. This approach is appropriate because many higher education institutions, especially in emerging higher education systems, are only beginning to integrate risk management, dashboards, institutional analytics, and predictive modelling into one governance system.

The object of the research is the university risk management system. The subject of the research is the organizational and analytical mechanisms through which universities can identify, assess, monitor, and predict risks using data.

The methodological basis of the study consists of several complementary approaches.

First, a literature review approach was used to examine international research on enterprise risk management in higher education, learning analytics, early warning systems, predictive analytics, and artificial intelligence in universities. Particular attention was paid to peer-reviewed publications with DOI identifiers.

Second, comparative analysis was used to compare traditional risk management and data-driven risk management. Traditional risk management usually relies on expert judgment, periodic reporting, qualitative risk matrices, and internal control procedures. Data-driven risk management additionally uses institutional data, digital traces, statistical models, machine learning algorithms, dashboards, and real-time monitoring.

Third, risk mapping was applied to classify university risks into key groups: academic risks, financial risks, operational risks, digital and cybersecurity risks, reputational risks, human resource risks, and strategic risks. This classification allows the development of risk indicators and predictive variables for each risk group.

Fourth, conceptual modelling was used to design an integrated framework for data-driven university risk management. The model is based on the logic of enterprise risk management, ISO 31000 principles, COSO ERM, the three lines model, and the practical requirements of university governance.

Fifth, an illustrative analytical matrix was developed to connect types of risks, data sources, key risk indicators, predictive methods, and management responses. The matrix is not based on confidential institutional data. It is designed as a demonstration tool showing how universities can operationalize data-driven risk management.

The general methodological logic of the study is presented in Table 1.

Table 1. Research design of the study

Research stage	Method used	Purpose
Literature analysis	Review of peer-reviewed studies	To identify existing approaches to ERM, analytics, and predictive models in higher education
Risk classification	System analysis and risk mapping	To group university risks into academic, financial, digital, operational, reputational, HR, and strategic categories
Indicator design	KRI/KPI approach	To develop measurable signals for monitoring risk exposure
Predictive logic	Conceptual modelling	To connect risk indicators with predictive models and early warning mechanisms
Framework development	Integrated ERM modelling	To propose a data-driven risk management framework for universities
Practical illustration	Demonstration risk scoring	To show how dashboards and thresholds may support decision-making
Note: Compiled by the authors		

The proposed framework can be empirically tested in future research through institutional data such as student information systems, learning management systems, financial systems, HR databases, internal audit reports, accreditation results, complaints registers, cybersecurity logs, and digital platform activity.

Results

The main result of the study is the development of a conceptual and applied framework for data-driven risk management in universities. The proposed framework consists of five interconnected components: risk data architecture, risk taxonomy, key risk indicators, predictive models, and governance response mechanisms.

1. Risk data architecture

The first component is the creation of university risk data architecture. Universities already generate large amounts of data, but these data are often stored in separate systems and are not used for integrated risk management. A data-driven approach requires connecting different data sources into one analytical environment.

Potential university risk data sources include:

- student information systems;
- learning management systems;
- financial management systems;
- HR databases;
- internal audit and compliance reports;
- accreditation and quality assurance results;
- cybersecurity logs;
- student feedback platforms;
- research performance databases;
- social media and public reputation indicators.

The purpose of data architecture is not to collect data for its own sake, but to transform fragmented information into risk signals. For example, declining attendance, low LMS activity, delayed assignment submission, and weak assessment results can become early signals of academic risk. Delays in payments, budget deviations, and increasing dependence on one source of funding can become signals of financial risk.

2. Risk taxonomy for data-driven university management

The second component is the development of a clear risk taxonomy. Without a structured classification of risks, data analytics cannot support management decisions effectively. The proposed taxonomy includes seven main risk groups (Table 2).

Table 2. Risk taxonomy for universities

Risk group	Examples of risks	Possible data sources
Academic risks	Dropout, low academic performance, curriculum mismatch, academic misconduct	Student records, LMS data, assessment results, accreditation reports
Financial risks	Budget deficit, unstable revenue, grant dependency, inefficient spending	Budget data, accounting systems, tuition payment data
Operational risks	Process failures, service delays, infrastructure problems	Administrative systems, service requests, internal control reports
Digital risks	Cyber incidents, data breaches, system downtime, weak digital infrastructure	IT logs, cybersecurity reports, platform availability data
Reputational risks	Negative media attention, low student satisfaction, ranking decline	Surveys, social media monitoring, ranking data, complaints
Human resource risks	Staff turnover, shortage of qualified academic staff, low motivation	HR databases, workload data, staff surveys
Strategic risks	Failure to achieve strategic goals, weak innovation, low research output	Strategic KPIs, research databases, project monitoring data
Note: Compiled by the authors		

This taxonomy shows that data-driven risk management should not be limited to student performance. A university is a complex organization; therefore, analytics should cover educational, financial, administrative, technological, reputational, and strategic dimensions.

3. Key Risk Indicators for universities

The third result is the development of key risk indicators. KRI are measurable indicators that show whether a risk is increasing, decreasing, or remaining stable. In traditional risk management, risks are often assessed qualitatively as “low,” “medium,” or “high.” In data-driven risk management, these assessments should be supported by measurable indicators and thresholds (Table 3).

Table 3. Examples of Key Risk Indicators for universities

Risk type	Key Risk Indicator	Risk signal
Academic risk	Percentage of students with low LMS activity during the first four weeks	Early risk of academic failure or dropout
Academic risk	Share of students with repeated failed assessments	Risk of poor learning outcomes
Financial risk	Share of revenue from one funding source	Risk of financial dependence
Financial risk	Budget deviation from planned expenditure	Risk of weak financial control
Digital risk	Number of cybersecurity incidents per semester	Risk of data security failure
Digital risk	System downtime hours per month	Risk of interruption in educational processes
HR risk	Staff turnover rate	Risk of loss of human capital
HR risk	Share of academic staff with excessive workload	Risk of burnout and quality decline
Reputational risk	Number of justified complaints from students	Risk of declining trust
Strategic risk	Percentage of strategic KPIs not achieved	Risk of poor strategic implementation
Note: Compiled by the authors		

The advantage of KRI is that they transform risk management into a measurable process. They also make it possible to introduce risk appetite and thresholds. For example, a university may set a threshold that system downtime should not exceed a certain number of hours per month, or that the share of students with low LMS activity should not exceed a defined level.

4. Demonstration of risk thresholds and scoring

To strengthen the practical application of the framework, this study proposes an illustrative risk scoring logic. The score is based on two dimensions: probability and impact. Each dimension is assessed on a scale from 1 to 5. The total risk score is calculated as:

Risk Score = Probability × Impact

The interpretation of the score may be organized as follows:

- 1-5: Low risk;
- 6-10: Moderate risk;
- 11-15: High risk;
- 16-25: Critical risk.

This scoring system can be integrated into a university dashboard and connected with KRI thresholds.

Table 4. Illustrative risk scoring matrix for a university

Risk area	Key indicator	Probability	Impact	Risk score	Risk level	Recommended response
Academic risk	22 % of first-year students show low LMS activity	4	4	16	Critical	Early warning intervention, academic advising, tutoring
Financial risk	48 % of revenue depends on one funding source	4	5	20	Critical	Revenue diversification, scenario planning
Digital risk	18 hours of system downtime per month	3	4	12	High	IT infrastructure review, backup systems
HR risk	17 % staff turnover in key departments	3	4	12	High	Retention strategy, workload review
Reputational risk	Increase in justified student complaints by 25 %	3	3	9	Moderate	Service quality review, communication measures
Strategic risk	35 % of strategic KPIs are behind target	4	4	16	Critical	Strategic plan adjustment, management review

Note: Compiled by the authors

The values in Table 4 are illustrative and are not based on confidential data of a specific university. They demonstrate how a university can transform raw institutional indicators into risk scores and management actions.

5. Predictive models in university risk management

The fifth result is the identification of predictive models that can be applied to university risk management. Predictive analytics can help universities move from describing past problems to forecasting future risks.

The following models can be used:

- logistic regression for predicting the probability of dropout or academic failure;
- decision trees for classifying risk groups;
- random forests for improving prediction accuracy;
- gradient boosting models for complex nonlinear patterns;
- time-series models for forecasting financial and enrollment trends;
- clustering models for identifying groups of students, staff, or departments with similar risk profiles;
- anomaly detection models for identifying unusual financial transactions, cybersecurity events, or operational failures.

For example, a dropout prediction model may use attendance, LMS activity, grades, assignment submission, financial status, and student support requests. A financial risk model may use budget execution, revenue concentration, tuition payment delays, and grant dependency. A reputational risk model may combine student satisfaction surveys, complaints, media monitoring, and ranking dynamics (Table 5).

Table 5. Application of predictive models to university risks

Risk area	Predictive model	Expected output	Management response
Student dropout	Logistic regression, random	Probability of dropout	Academic advising, tutoring, psy-

	forest		chological support
Financial instability	Time-series forecasting	Expected budget gap	Budget correction, diversification of revenue
Cybersecurity	Anomaly detection	Unusual system activity	IT response, access control, incident investigation
Staff turnover	Classification models	Probability of resignation	Workload review, retention measures
Reputational decline	Sentiment analysis	Negative sentiment trend	Communication strategy, service improvement
Strategic underperformance	KPI forecasting	Probability of non-achievement	Strategic plan correction
Note: Compiled by the authors			

Predictive models should not replace managerial judgment. They should support decision-making by providing earlier and more objective risk signals.

6. Integrated framework for data-driven ERM

The final and most important result is the proposed integrated framework for data-driven ERM in universities.

The framework includes the following logic:

1. Data collection from university systems.
2. Data cleaning and integration into a risk data environment.
3. Risk classification according to the university risk taxonomy.
4. KRI calculation for each risk group.
5. Predictive modelling to identify future risk exposure.
6. Dashboard visualization for management bodies.
7. Governance response through risk owners, committees, internal control, and strategic planning.
8. Monitoring and feedback to improve the model.

7. Early warning dashboard logic

The proposed framework can be implemented through an early warning dashboard. The dashboard should not only present data but also show risk status, thresholds, responsible units, and required management responses (Table 6).

Table 6. Example of early warning dashboard logic

Dashboard block	Main question	Example output
Academic risk block	Which students or programs show early signs of failure?	List of programs with high share of low LMS activity
Financial risk block	Are revenue and expenditure within acceptable limits?	Budget deviation and revenue concentration indicators
Digital risk block	Are digital systems stable and secure?	Downtime hours, cyber incidents, unresolved IT tickets
HR risk block	Are there signs of staff instability?	Turnover rate, workload pressure, vacancy duration
Reputational risk block	Is stakeholder trust weakening?	Complaints, satisfaction scores, media sentiment
Strategic risk block	Are strategic goals being achieved?	KPI completion rate and forecasted non-achievement
Note: Compiled by the authors		

The dashboard should use three levels of warning:

- Green zone: risk is within appetite;
- Yellow zone: risk is approaching the threshold;
- Red zone: risk exceeds the acceptable level and requires immediate management action.

Discussion

The findings of the study confirm the hypothesis that the integration of analytics, predictive models, and ERM instruments can improve the timeliness, accuracy, and strategic relevance of university risk management. Traditional risk management systems in universities often depend on periodic reports, expert judgment, and internal audit findings. Although these instruments remain important, they are not sufficient in the context of University 4.0, where risks emerge quickly and are strongly connected with digital platforms, data flows, and stakeholder expectations.

The proposed framework contributes to the literature in several ways. First, it connects two research areas that are often discussed separately: enterprise risk management in higher education and learning analytics. Existing studies on learning analytics mainly focus on student performance, dropout, and academic success. Existing studies on risk management mainly focus on governance, control, risk registers, and institutional accountability. This article brings these directions together and shows that learning analytics can become part of a broader institutional ERM system.

Second, the study expands the meaning of data-driven risk management beyond student analytics. While student dropout remains one of the most important areas for predictive modelling, universities also face financial, digital, operational, HR, reputational, and strategic risks. Therefore, a comprehensive data-driven ERM system should cover not only educational data but also financial data, HR data, IT data, quality assurance data, and strategic performance indicators.

Third, the study emphasizes the importance of governance. Predictive models have limited value if they are not connected with decision-making procedures. For example, identifying a student at risk is useful only if the university has a clear intervention process. Forecasting financial instability is useful only if management has mechanisms for budget correction. Detecting cybersecurity anomalies is useful only if the IT department and risk owners have clear response protocols.

Fourth, the study highlights the ethical dimension of data-driven risk management. Universities must ensure that predictive models are transparent, fair, and compliant with personal data protection requirements. The use of student and staff data requires clear rules on access, consent, anonymization, storage, and accountability. A data-driven university should not become a surveillance-based organization. Instead, analytics should be used to support students, protect institutional sustainability, and improve management quality.

The proposed framework is particularly relevant for universities in Kazakhstan. The national higher education system is undergoing transformation through digitalization, academic autonomy, quality assurance reforms, and stronger competition. In this context, universities need not only formal risk registers but also measurable indicators, dashboards, and predictive tools. This is consistent with the broader idea that risk management should be integrated into university governance, strategic planning, and internal control.

The results are also consistent with the international literature. Studies on learning analytics confirm that educational data can help identify at-risk students and support timely interventions (Siemens, 2013); (Bañeres et al., 2020). Research on predictive models confirms that different statistical and machine learning approaches can support student success forecasting (Cui et al., 2019). Studies on artificial intelligence in higher education show that digital tools are increasingly used in educational management, but require stronger institutional and ethical governance (Zawacki-Richter et al., 2019). Research on risk management in higher education confirms the importance of systematic risk governance and further development of risk management practices (Khaw & Teoh, 2023).

However, this study goes beyond previous literature by proposing a broader institutional model. It does not limit analytics to student performance, but connects data-driven tools with enterprise risk management, risk appetite, KRI, dashboards, predictive models, and management response mechanisms.

The study has several limitations. Since the article develops a conceptual-applied model, it does not test the framework on primary institutional data. Future research should apply the proposed framework in a specific university, collect real data from LMS, finance, HR, and internal control systems, and test the predictive accuracy of selected models. It would also be useful to compare different machine learning algorithms and evaluate their interpretability, fairness, and practical usefulness for university management.

Conclusion

This study developed a conceptual and applied framework for data-driven risk management in universities. The research showed that modern universities require a transition from fragmented and reactive risk control to integrated, measurable, and predictive ERM systems. The proposed framework combines risk data architecture, risk taxonomy, key risk indicators, predictive models, dashboards, and governance mechanisms.

The study achieved its main objective by demonstrating how analytics and predictive models can be embedded into university risk management. The proposed approach allows universities to identify risks earlier, monitor risk exposure through measurable indicators, predict potential negative outcomes, and support evidence-based managerial decisions.

The main scientific novelty of the study lies in integrating enterprise risk management and predictive analytics into a single data-driven risk management framework for universities. Unlike traditional approaches, the proposed model treats risk management not only as a compliance or internal control function but also as a strategic analytical system.

The practical value of the study is reflected in the proposed taxonomy of university risks, examples of KRI, risk thresholds, risk scoring matrix, and the model connecting risks with data sources, predictive models, dashboards, and management responses. These instruments can be used by university management, internal audit units, quality assurance departments, strategic planning offices, and risk owners.

The hypothesis of the study is confirmed at the conceptual level: the integration of data analytics, predictive models, and ERM instruments can improve the timeliness, accuracy, and strategic value of university risk management. However, empirical testing is required to validate the proposed framework using real institutional data.

For practical implementation, universities are recommended to:

1. develop a unified risk data architecture;
2. introduce a university-wide risk taxonomy;
3. define KRI and risk appetite thresholds;
4. implement dashboards for risk monitoring;
5. pilot predictive models for academic, financial, digital, HR, and reputational risks;
6. assign risk owners and response procedures;
7. ensure ethical and legal protection of personal data;
8. integrate data-driven risk reports into strategic governance.

Thus, data-driven risk management can become an important mechanism for strengthening institutional resilience, improving decision-making, and supporting the sustainable development of universities in the era of University 4.0.

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Аңдатпа

Қазіргі университеттер цифрлық трансформация, қаржылық тұрақсыздық, демографиялық өзгерістер, студенттер мен академиялық кадрлар үшін бәсекелестік және киберқауіптер, сондай-ақ реттеуші органдар мен қоғам тарапынан артып келе жатқан талаптар тудырған белгісіздік жағдайында жұмыс істейді. Жоғары білім беру саласындағы дәстүрлі тәуекелдерді басқару көбінесе бытыраңқы, жағдайға қарай әрекет ететін және стратегиялық шешімдер қабылдаумен жеткілікті деңгейде байланыспаған сипатта болады. Зерттеу мақсаты — университеттерде деректерге негізделген тәуекелдерді басқарудың тұжырымдамалық-қолданбалы моделін әзірлеу, яғни enterprise risk management, key risk indicators, dashboards, learning analytics және болжамдық модельдерді біріктіру. Зерттеу тұжырымдамалық-қолданбалы сипатқа ие және жоғары білімдегі тәуекелдерді басқару, оқыту аналитикасы, ерте ескерту жүйелері, болжамдық аналитика және цифрлық басқару бойынша халықаралық ғылыми әдебиеттерді талдауға негізделген. Әдістемелік негіз ретінде жүйелік талдау, салыстырмалы талдау, тәуекел картасын құру, жетілу деңгейін бағалау және тұжырымдамалық модельдеу қолданылды. Зерттеу нәтижесінде бес компоненттен тұратын деректерге негізделген ERM моделі ұсынылды: тәуекел деректерінің архитектурасы, тәуекелдер таксономиясы, негізгі тәуекел индикаторлары, болжамдық модельдер және басқарушылық жауап беру механизмдері. Сонымен қатар академиялық, қаржылық, цифрлық, кадрлық, операциялық және беделдік тәуекелдер бойынша тәуекел индикаторлары, шекті мәндер және тәуекелдерді бағалау матрицасы ұсынылды. Зерттеу нәтижелері аналитика мен болжамдық модельдер университеттердегі тәуекелдерді басқаруды формальды бақылау функциясынан проактивті, өлшенетін және дәлелдерге негізделген басқару жүйесіне айналдыра алатынын көрсетеді. Ұсынылған модель Қазақстан университеттерінде тәуекелдерді ерте анықтау, стратегиялық жоспарлау және институционалдық тұрақтылықты арттыру үшін қолданылуы мүмкін.

Кілт сөздер: мәліметтер негізіндегі тәуекелдерді басқару, университеттер, болжау модельдері, оқу аналитикасы, кәсіпорын тәуекелін басқару.

Управление рисками в университетах на основе данных: применение аналитики и прогнозных моделей

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Аннотация

Современные университеты функционируют в условиях возрастающей неопределенности, вызванной цифровой трансформацией, финансовой нестабильностью, демографическими изменениями, конкуренцией за студентов и академические кадры, киберугрозами, а также ростом требований со стороны регуляторов и общества. Традиционное управление рисками в системе высшего образования часто остается фрагментарным, реактивным и недостаточно связанным со стратегическим принятием решений. Целью данного исследования является разработка концептуально-прикладной модели управления рисками в университетах на основе данных путем интеграции enterprise risk management, ключевых индикаторов риска, управленческих панелей, learning analytics и прогнозных моделей. Исследование имеет концептуально-прикладной характер и основано на обзоре международной литературы по риск-менеджменту, обучающей аналитике, системам раннего предупреждения, прогнозной аналитике и цифровому управлению в высшем образовании. Методологическую основу составили системный анализ, сравнительный анализ, картирование рисков, оценка зрелости и концептуальное моделирование. В результате предложена интегрированная data-driven ERM-модель, включающая пять компонентов: архитектуру риск-данных, таксономию рисков, ключевые индикаторы риска, прогнозные модели и механизмы управленческого реагирования. Также представлены примеры индикаторов, пороговых значений, матрицы оценки рисков и применения прогнозных моделей для академических, финансовых, цифровых, кадровых, операционных и репутационных рисков. Полученные результаты показывают, что аналитика и прогнозные модели позволяют трансформировать риск-менеджмент университета из формальной контрольной функции в проактивную, измеримую и доказательную систему управления. Практическая значимость исследования заключается в возможности применения предложенной модели в университетах Казахстана для раннего выявления рисков, стратегического планирования и повышения институциональной устойчивости.

Ключевые слова: управление рисками на основе данных, университеты, предиктивные модели, аналитика обучения, корпоративное управление рисками.

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Conflict of Interest

The authors declare no conflict of interest.