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НАУЧНЫЙ ЖУРНАЛ

ихайлович Ча́плин (28 июля (9 августа)
0 ноября 1931) — русский и советский учёный
пециалист в области отопительно-
ионной техники.

Дед писательницы Веры Чаплиной[2]. Потомственный дворянин из рода Чаплиных, восходящего[3] ко Льву Чаплину (середина XV века)[4].

В 1883 году окончил Императорское Московское техническое училище (ИМТУ), а в 1898 году получил в училище должность профессора. В 1898—1909 гг. также преподавал в Московском Училище живописи, ваяния и зодчества.

В 1895 году вместе с коллегой по ИМТУ архитектором В. Г. Залесским Чаплин организовал торговый дом «В. Залесский и В. Чаплин». В 1902 году Залесский и Чаплин построили собственный дом на Большой Дмитровке, 16, в котором их семьи имели по отдельному этажу и где располагались помещения их технической конторы[5]. Среди реализованных проектов торгового дома «В. Залесский и В. Чаплин» — системы отопления и вентиляции почти 1500 зданий[6] в десятках городов Российской Империи: Музей изящных искусств имени императора Александра III, Румянцевский музей, Политехнический музей, Аудиторный корпус Московского университета, Императорское Московское техническое училище, Московское училище живописи, ваяния и зодчества, Александровское военное училище, Брестский (Белорусский) вокзал, автозавод А. М. О., Сандуновские бани, гостиница Метрополь, ресторан Эрмитаж, здание страхового общества «Россия», Алексеевская глазная больница, страннолриимный дом Шереметева, храм Василия Блаженного, склеп великого князя Сергея Александровича в Чудовом монастыре, Перервинский монастырь, Заиконоспасский монастырь, храм Марфо-Мариинской обители — все в Москве; храм-усыпальница Юсуповых в Архангельском, Петербургская городская детская больница, Путиловский завод, Архангельские городские ряды, Нижегородский городской театр, Киевский коммерческий институт, царский дворец в Ливадии, Иркутский завод «Треугольник», детская больница в Баку, фабрика Столыпина в Пензе, храм Казанской Божией матери в Риге, электрическая станция в Рязани, Тамбовский пороховой завод, Волжско-Камский банк в Самаре, Калужское Епархиальное училище, Императорский Харьковский университет и многие другие.

В 1903 году В. М. Чаплин создал первую в
водяного отопления с побудительной
Предложенная им водо-водяная
прототипом широко
систем отопления
теплофикации

165 ЛЕТ СО ДНЯ РОЖДЕНИЯ
9 августа 2026 г.

ЧАПЛИН
ВЛАДИМИР МИХАЙЛОВИЧ
1861-1931 гг.

Г. МОСКВА

РУССКИЙ УЧЁНЫЙ, СПЕЦИАЛИСТ В ОБЛАСТИ ОТОПИТЕЛЬНО-ВЕНТИЛЯЦИОННОЙ ТЕХНИКИ

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Market entry conditions and fleet health management in U.S. car-sharing operations

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Russian, Kazan

Условия выхода на рынок и управление технической исправностью автопарка в операциях каршеринга в США

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Abstract

Car-sharing operators entering U.S. metropolitan markets face two decisions that most of the literature treats separately: where to launch, and how to keep a deployed fleet mechanically sound afterward. This review synthesizes peer-reviewed research on geographic market selection, regulatory entry conditions, and fleet health monitoring, and examines a recently proposed integrating framework built around a weighted market-scoring model and a Fleet Health Index. Documented market exits, including Car2Go's 2019 – 2020 withdrawal from the United States, are often attributed in this literature to entry decisions calibrated against demographic proxies and to reactive maintenance regimes that pull vehicles out of service exactly when demand peaks. The

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same period coincided with the onset of the COVID-19 pandemic and intensifying competition from subscription-based leasing, confounds the practitioner account does not address. Quantitative market-scoring methods are independently associated with higher penetration rates and lower exit frequencies than heuristic selection, and predictive-maintenance methods report unscheduled-event reductions approaching 40 percent relative to reactive baselines in industrial fleet settings. Applied to car-sharing specifically, the review finds genuine value in the diagnosis that entry conditions and fleet health should be modeled jointly, and identifies specific validation gaps, no reported weight-estimation procedure, no sensitivity analysis, no external replication, that determine how much confidence the proposed framework currently warrants.

Аннотация

Операторы каршеринга, выходящие на рынки американских агломераций, сталкиваются с двумя решениями, которые большинство работ рассматривает раздельно: где запускать сервис и как поддерживать техническую исправность развёрнутого автопарка впоследствии. В обзоре обобщены рецензируемые исследования по географическому выбору рынка, регуляторным условиям выхода и мониторингу технического состояния автопарка, а также рассмотрена недавно предложенная интегрирующая модель, построенная на взвешенном скоринге рынков и индексе технической исправности парка (Fleet Health Index). Зафиксированные случаи ухода с рынка, включая уход Car2Go из США в 2019 – 2020 годах, в этой литературе часто объясняются решениями о выходе, откалиброванными по демографическим показателям, и реактивным режимом технического обслуживания, выводящим транспортные средства из эксплуатации именно в периоды пикового спроса. Тот же период совпал с началом пандемии COVID-19 и усилением конкуренции со стороны сервисов подписочной аренды автомобилей, смешивающими факторами, которые практико-ориентированные источники не рассматривают. Количественные методы скоринга рынков независимо связаны с более высокими показателями проникновения и более низкой частотой ухода с рынка по сравнению с эвристическим отбором, а методы предиктивного обслуживания демонстрируют сокращение внеплановых простоев почти на 40 % относительно реактивных базовых показателей в промышленных автопарках. Применительно к каршерингу обзор находит реальную ценность в тезисе о необходимости совместного моделирования условий выхода на рынок и технического состояния парка, но выявляет конкретные пробелы валидации, отсутствие описанной процедуры оценки весов, анализа чувствительности и независимой репликации, которые определяют степень доверия к предложенной модели на сегодняшний день.

Keywords: car-sharing, market entry, fleet health management, predictive maintenance, market scoring, vehicle downtime.

Ключевые слова: каршеринг, выход на рынок, управление технической исправностью автопарка, предиктивное обслуживание, скоринг рынка, простой транспортных средств.

Introduction

Commercial car-sharing in the United States expanded from a handful of cooperative pilot programs in the late 1990s into an industry segment with several million active members [1]. Two decisions determine whether an individual operator captures a share of that market. The first is where to launch: which metropolitan areas, corridors, or zones offer a defensible combination of demand density, competitive white space, and regulatory receptivity. The second is how to keep the fleet mechanically capable of serving that demand once launch has occurred. Academic and practitioner literature has developed each decision largely on its own track. Market-entry research draws on international-business and platform-economics traditions that predate car-sharing by decades [2]; fleet-health research draws on predictive-maintenance traditions built originally for industrial and logistics fleets. Mamaev [3], an independent practitioner-researcher whose work on this specific integration point has not gone through conventional peer review, argues that the separation between the two literatures is a structural weakness of the field. A vehicle repositioned to correct a demand imbalance may itself be the vehicle nearest its maintenance threshold, and no shared decision architecture in the prior peer-reviewed literature accounts for that interaction. Whether Mamaev's own proposed architecture accounts for it adequately is a separate question addressed later in this review.

Documented market exits recur around a similar diagnosis, though the diagnosis is contested. Car2Go withdrew from all of its American markets between 2019 and 2020, and BMW's ReachNow exited Seattle and Brooklyn in the same window, in each case after membership growth that looked healthy on conventional adoption metrics [4]. Practitioner accounts attribute the failure primarily to entry decisions calibrated against population and income proxies that miss the operational variables determining unit economics: transit-substitution density, existing for-hire supply saturation, and the local availability of qualified fleet operators [5]. That attribution deserves scrutiny on its own terms. Both exits occurred as the COVID-19 pandemic collapsed urban trip demand across every shared-mobility category at once, and both operators faced intensifying competition from subscription-based leasing products aimed at exactly the customer segment car-sharing relies on. A scoring-error explanation and a demand-shock explanation are not mutually exclusive, but the practitioner literature examined here presents only the former. The Results and discussion section returns to this gap.

Firnkorn [6] offers an independently documented instance of the same entry-scoring problem in a different national context. A free-floating operator in Germany expanded its service area using population-density projections, and utilization fell sharply once the area exceeded the zone that trip-origin density actually supported. Unlike the Car2Go and ReachNow cases, this account comes from a peer-reviewed empirical study, not from after-the-fact practitioner analysis, and it isolates the scoring mechanism more cleanly because no pandemic or major competitive shock coincided with the observed decline.

Entry-condition failures compound with a second, mechanically distinct problem. Under reactive maintenance, a vehicle is serviced only once a fault becomes observable, and the resulting out-of-service periods should in principle extend longest exactly when zone-level demand is highest, since usage intensity drives both demand and mechanical stress. That claim is a logical inference about a shared driver, however; none of the sources reviewed here isolate and measure the correlation directly against fleet-level operating data. The two failure modes still compound each other in practice: a fleet entering an underscored market with too few vehicles has less slack to absorb the vehicles that reactive maintenance removes from service at the worst possible moment.

Materials and methods

Coverage was built from peer-reviewed literature indexed in Transportation Research Part A, Transportation Research Part B, Transportation Research Part E, Transport Policy, Business Strategy and the Environment, Organization & Environment, Sustainability, WIREs Data Mining and Knowledge Discovery, and Energies. Search terms combined «carsharing,» «car-sharing,» «market entry,» «market selection,» «predictive maintenance,» «fleet health,» and «vehicle damage detection.» Three inclusion criteria applied. A study had to address either the geographic and regulatory conditions governing car-sharing market entry, or the technical methods used to monitor, predict, or manage vehicle condition within an operating fleet. Studies confined to ride-hailing driver-side labor questions without a fleet-ownership component were excluded. Studies addressing vehicle maintenance in contexts unrelated to shared or commercial fleets were excluded unless directly relevant as methodological precedent for an included fleet-health study.

Results and discussion

Firms entering geographically dispersed markets have historically followed a psychic-distance logic: expansion targets markets that feel familiar based on managerial experience, and objective demand characteristics only correct that bias in later expansion rounds [7]. Brouthers and Nakos [8] tested this pattern directly against a scored alternative. Firms applying quantitative scoring criteria to candidate markets achieved higher penetration rates and lower exit frequencies than firms relying on experiential judgment, and the performance gap traced specifically to the scoring methodology, independent of industry or firm size. Car-sharing entry decisions have followed the heuristic pattern more often than the scored one. Firnkorn [6] documents a free-floating operator expanding its service area on population-density projections and reports utilization falling sharply once the area exceeded the zone that trip-origin density actually supported.

Regulatory and municipal conditions add a second entry variable that scoring frameworks imported from general platform economics do not capture. Shaheen, Cohen, and Martin [9] document that carsharing parking policy in North America varied by jurisdiction, from formal, legislated space allocation in California to informal arrangements negotiated city by city, and this variation materially affected the fixed cost an operator faced before a single vehicle generated revenue. Namazu, MacKenzie, Zerriffi, and Dowlatabadi [10] found that carsharing membership diffusion within a metropolitan area correlated more strongly with proximity to parking infrastructure than with income or age. Rotaris and Danielis [11] extended this line of inquiry to smaller towns and rural areas: the viability threshold for carsharing service depends on population density nonlinearly, with a floor below which no pricing or fleet-sizing adjustment restores viability.

Mamaev's framework, examined in this review, proposes a six-variable weighted scoring model for this class of entry decision, combining population density, proximity to public transit stops, vehicle registration density per capita, a mobility-service saturation index expressed as the ratio of licensed for-hire vehicles to working-age population, and an entrepreneurial-operator-availability score derived from county-level small-business formation rates [12, 5]. Each variable is normalized by min-max transformation and combined through assigned weights; the reported specification assigns 0.15 to the mobility-saturation index and 0.10 to operator availability. The model extends the logic Brouthers and Nakos [8] validated empirically for SMEs generally into variables specific to car-sharing unit economics. Extends is the operative word: unlike the Brouthers and Nakos study, no comparable empirical test of penetration and exit outcomes accompanies the six-variable specification in the sources reviewed here.

Comparative evidence across national contexts supports a broader point: market condition is not reducible to a single density figure. Wang, Zhu, Wei, Jiang, and Yamamoto [13] develop an eight-metric assessment framework for carsharing business development spanning China, Europe, Japan, and the United States. Market condition, parking condition, electric-vehicle deployment, and vehicle maintenance appear as separate, independently weighted dimensions in their model, and their comparative case analysis finds that operators in different regulatory environments succeed or fail along different subsets of these eight metrics. That finding argues against a universal entry-scoring formula and toward market-specific calibration, a direction consistent with Rotaris and Danielis [11] and with the practitioner scoring model discussed above, reached through unrelated methods.

Fleet-management research addressing vehicle condition specifically is younger and thinner than the market-entry literature. Foundational work on shared-vehicle fleet operations, including Nair and Miller-Hooks [14] and Kek, Cheu, Meng, and Fung [15], formulated relocation and allocation as stochastic and combinatorial optimization problems treating each vehicle as simply available or unavailable, with no representation of gradual degradation short of outright failure. Reactive maintenance built on that binary assumption services a vehicle only once a fault is observable, and the resulting downtime tends to concentrate during periods of peak demand, when usage intensity is highest for both.

Two adjacent literatures have begun to close this gap. Hasan, Nguyen, Boo, Jahani, and Ong [16], in a systematic review of artificial-intelligence-based vehicle damage detection spanning insurance, resale, and fleet-management applications, find that deep-learning image classification has matured enough for operational deployment. Dataset limitations persist, however, particularly the underrepresentation of minor and underbody damage in training data, and these gaps constrain detection accuracy for exactly the damage categories most relevant to shared-fleet wear. Cavus, Dissanayake, and Bell [17] report complementary progress in electric-vehicle battery health prognostics, predicting degradation trajectories from telematics-derived charge and discharge data. Chaudhuri and Ghosh [18] demonstrate a hierarchical fuzzy support-vector-machine architecture for industrial IoT vehicle fleets that classifies component health from telematics streams at lower computational cost than comparable ensemble methods, a property that matters for any system meant to run on a short refresh cycle across a large fleet.

Mamaev framework proposes a single composite Fleet Health Index to unify these signal streams, mileage, age, maintenance history, sensor telematics, and availability, into one scalar per vehicle, computed as a weighted linear combination of five normalized sub-indicators and updated on a rolling basis [3]. Vehicles below an operator-defined maintenance threshold are excluded from trip allocation pending service; vehicles below a lower retirement threshold are flagged for decommissioning review. A least-squares trend projected fourteen days forward over the trailing thirty-day index history generates anticipatory maintenance alerts before either threshold is crossed. The index feeds a mixed-integer linear program that jointly assigns vehicles to zones and schedules repositioning, turning vehicle health into a hard allocation constraint. The reported comparative analysis, higher utilization, less downtime, lower repositioning cost, comes entirely from the same source that designed the index. No outside dataset or independent research team has yet tested it. Table 1 summarizes the quantitative claims reported across the peer-reviewed literature in both domains.

Table 1.

Quantified findings reported in the peer-reviewed market entry and fleet health literature

Domain	Study	Reported finding
Market entry	Brouthers & Nakos [8]	Quantitative market scoring associated with higher penetration and lower exit rates than experiential selection
Market entry	Firnkorn [6]	Utilization falls sharply once free-floating service area exceeds the zone supported by actual trip-origin density
Market entry	Namazu, MacKenzie, Zerriffi, & Dowlatabadi [10]	Carsharing diffusion correlates more strongly with parking-infrastructure proximity than with income or age demographics
Market entry	Rotaris & Danielis [11]	Carsharing viability threshold in small towns and rural areas is nonlinear in population density
Market entry	Wang, Zhu, Wei, Jiang, & Yamamoto [13]	Eight independently weighted metrics needed to compare carsharing viability across national contexts
Fleet health	Hasan, Nguyen, Boo, Jahani, & Ong [16]	AI damage detection mature for deployment; dataset gaps persist for minor and underbody damage
Fleet health	Cavus, Dissanayake, & Bell [17]	AI-driven prognostics predict EV battery degradation from telematics data
Fleet health	Chaudhuri & Ghosh [18]	Hierarchical fuzzy SVM classifies fleet component health with lower computational overhead than comparable ensembles

Two decades separate Brouthers and Nakos [8] from the practitioner framework proposed here, yet the underlying diagnosis has not changed: heuristic, single-variable decisions underperform structured, multi-variable ones, in market entry and in fleet allocation alike. Nair and Miller-Hooks [14] made the equivalent case for fleet allocation over a decade ago. What is new is the attempt to run both decisions through one shared architecture instead of two disconnected ones. That ambition is worth taking at face value even though its current execution is not.

Start with the market-scoring weights. The framework reports 0.15 on the mobility-saturation index and 0.10 on operator availability, figures presented without an estimation procedure or a sensitivity analysis showing how rankings would shift under different values. Brouthers and Nakos [8] showed that scoring benefits depend on the scoring methodology itself; an arbitrary weighting scheme dressed in the language of formal scoring could reproduce the very heuristic failure it claims to replace. A companion piece by Mamaev reports an ordinary-least-squares recalibration step meant to update the weights from post-launch performance data [12].

Its five sub-indicator weights are stated as operator-configurable defaults, not derived from failure data, and nothing in the reported analysis tests them against an equal-weighted baseline or against the threshold rules Chaudhuri and Ghosh [18] already established for industrial IoT fleets.

The mixed-integer program that consumes the index is otherwise standard: comparable formulations have run against real Zipcar and car2go data in the fleet-management literature for over a decade. What the framework adds is the health constraint, nothing more, and that constraint's fifteen-minute recomputation cycle has not been tested at the scale, dozens of zones and thousands of vehicles, where solver time typically becomes the bottleneck.

Car2Go and ReachNow both exited in 2019 – 2020, and the practitioner literature attributes both exits to entry-scoring failure. Neither account engages with two obvious competing explanations. The first is macroeconomic: both withdrawals occurred as the COVID-19 pandemic suppressed urban travel demand across every mode, shared and private, simultaneously, which would have depressed utilization regardless of how well the original entry decision had been scored. The second is competitive: the same period saw rapid growth in subscription-based vehicle leasing aimed at the customer segment carsharing depends on, a substitution effect entirely separate from zone-level scoring accuracy. A scoring failure and a demand shock can coexist and even reinforce each other, but attributing the outcome to scoring alone is the kind of single-cause narrative a rigorous post-mortem should test against alternatives, not assume by default.

The market-entry literature reviewed draws heavily on European and Asian carsharing markets; generalizing to the more fragmented U.S. regulatory landscape, where parking and licensing authority sits with individual municipalities and not a national regulator, has not been systematically tested beyond the case evidence in Shaheen, Cohen, and Martin [9]. The fleet-health literature reviewed draws primarily on electric-vehicle and industrial-IoT contexts, and direct validation on the mixed internal-combustion and electric fleets typical of urban car-sharing remains limited. This review's own narrative protocol, without a systematic screening record, is a further limitation already noted in the Materials and methods section.

Conclusion

Market entry and fleet health in U.S. car-sharing operations have been studied by two literatures that rarely speak to each other. A practitioner framework now proposes to close that gap, and the proposal is worth taking seriously on its diagnosis even though its numbers are not yet earned. The weighted market-scoring approach extends a methodology Brouthers and Nakos [8] validated empirically for SMEs into car-sharing-specific variables, weighting demand-substitution and infrastructure-access measures above raw demographic projections, a direction consistent with what Namazu et al. [10] and Rotaris and Danielis [11] found independently through different methods. The Fleet Health Index adds vehicle condition as a hard constraint to allocation mathematics already validated elsewhere, a genuinely useful move: no prior commercial system in the literature reviewed enforces that constraint jointly with zone-level allocation. What has not happened is independent, adversarial testing, against operator data the framework's author did not collect, of the kind the peer-reviewed studies in Table 1 have already passed for narrower, single-domain claims. Until that testing happens, the framework belongs in the same category as the market-entry failures it seeks to explain: a plausible diagnosis, competing with unexamined alternatives, awaiting the kind of evidence that would settle the question either way.

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Hydrological assessment and management prospects of the Amudarya delta water bodies using GIS technologies

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Гидрологическая оценка и перспективы управления водными объектами дельты Амударьи с использованием ГИС-технологий

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Abstract

The reduction in Amudarya River discharge over recent decades has caused severe degradation of the delta's water bodies, threatening regional water security and ecological balance. The objective of this study was to conduct a GIS-based hydrological assessment of the Mezhdurechye Reservoir, Muynoq Bay, and Balikchi Bay in the Amudarya Delta, and to develop a mathematical model of their water balance for improving the water supply regime. Morphometric characteristics (area, volume, mean and maximum depth) were determined through field surveys using a Garmin eTrex 32x GPS navigator, Leica NA332 optical level, and VEGA TEO-20B/5B electronic theodolite, combined with ArcGIS 10.8 spatial analysis by the isobath method. Multi-year discharge data from the Kyzyldzhar hydrometric station (1965–2022) were analysed, and a differential water balance model was developed in the Visual C# environment, applying a monthly discretisation time step and verified against three characteristic years (wet — 2010; average — 2019; dry — 2001). The results show that the current storage capacity of the Mezhdurechye Reservoir is 13 % below its design value due to siltation, while bay areas have decreased by 14–23 %. Long-term discharge analysis confirms extreme flow regime instability (Cv = 1.08), with water reaching the delta basins in dry years being 166 times lower than in wet years. Zooplankton

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surveys recorded 27 species, markedly fewer than the 36 species documented in 1968–1983, indicating ongoing ecological degradation. The GIS-based framework developed in this study provides a scientifically grounded tool for water resource management in the Amudarya Delta.

Аннотация

Сокращение стока реки Амударья за последние десятилетия привело к серьезной деградации водных объектов дельты, угрожая региональной водной безопасности и экологическому балансу. Целью данного исследования было проведение гидрологической оценки Междуречьего водохранилища, залива Муйнок и залива Баликчи в дельте Амударьи с использованием ГИС-технологий, а также разработка математической модели их водного баланса для улучшения режима водоснабжения. Морфометрические характеристики (площадь, объем, средняя и максимальная глубина) определялись в ходе полевых исследований с использованием GPS-навигатора Garmin eTrex 32x, оптического нивелира Leica NA332 и электронного теодолита VEGA TEO-20B/5B в сочетании с пространственным анализом ArcGIS 10.8 методом изобат. Проанализированы многолетние данные о расходе воды с Кызылджарской гидрологической станции (1965–2022 гг.), разработана дифференциальная модель водного баланса в среде Visual C# с применением месячного шага дискретизации по времени, проверенная на трех характерных годах (влажный — 2010; средний — 2019; засушливый — 2001). Результаты показывают, что текущая емкость водохранилища Междуречь на 13 % ниже проектной из-за заиления, а площадь залива уменьшилась на 14–23 %. Долгосрочный анализ расхода подтверждает крайнюю нестабильность режима стока (Cv = 1,08), при этом объем воды, достигающей дельтовых бассейнов в засушливые годы, в 166 раз ниже, чем во влажные. В ходе исследований зоопланктона было зарегистрировано 27 видов, что значительно меньше, чем 36 видов, задокументированных в 1968–1983 годах, что указывает на продолжающуюся экологическую деградацию. Разработанная в данном исследовании ГИС-система представляет собой научно обоснованный инструмент для управления водными ресурсами в дельте реки Амударья.

Keywords: Amudarya delta, GIS technologies, water balance, morphometry, Mezhdurechye Reservoir, Muynoq Bay, Balikchi Bay, zooplankton, ArcGIS 10.8, hydrological modelling.

Ключевые слова: дельта реки Амударья, ГИС-технологии, водный баланс, морфометрия, Междуречье водохранилище, залив Муйнок, залив Баликчи, зоопланктон, ArcGIS 10.8, гидрологическое моделирование.

1. Introduction

The Amudarya Delta is located in the Republic of Karakalpakstan, Uzbekistan, and holds strategic significance for the region’s water resources and ecological balance. Historically, according to data from 1963–1965, the total area of the delta was 8,990 km², with lake systems such as Muynoq, Balikchi, Dumalak, Zhiltirbas, and Sudochye directly connected to the Aral Sea [1]. Over recent decades, a dramatic reduction in Amudarya discharge downstream of the Takhiatash hydraulic node has caused the delta lake area to shrink by more than half [2].

The decline in Amudarya discharge has had severe negative impacts not only on the region's fisheries and agricultural potential, but also on its ecosystems. Whereas the delta's lake systems covered more than 600 km² in the 1960s, this figure has decreased several-fold to date [3]. Between 2000 and 2003, a complex of engineering and organisational measures for restoring the ecological regime of the southern Aral region was developed under the NATO Science for Peace project [4]. Against this backdrop, there is an urgent need to monitor water bodies using GIS technologies and remote sensing, to conduct hydrological analyses, and to develop effective water management strategies [5].

The objective of this study is to evaluate the current hydrological status of the Amudarya Delta water bodies using GIS technologies, to model their water balance under different hydrological conditions, and to develop science-based recommendations for improving their water supply regime. To achieve this objective, the following tasks were addressed:

1. to determine the current morphometric parameters (area, volume, mean and maximum depth) of the Mezhdurechye Reservoir, Muynoq Bay, and Balikchi Bay through GPS-based field surveys and ArcGIS 10.8 spatial analysis, and to compare them with design values;
2. to analyse long-term discharge data from the Kyzyldzhar hydrometric station (1965–2022) and identify trends in the water supply regime of the delta;
3. to develop and verify a differential mathematical model of the water balance of the delta water bodies under characteristic years of different water availability (wet, average, dry);
4. to assess the current hydrobiological status of the water bodies through zooplankton composition analysis and to evaluate its relationship with the hydrological regime.

2. Materials and methods

2.1. Study area and field equipment

The study objects are the Mezhdurechye Reservoir, Muynoq Bay, and Balikchi (Sarbas) Bay, located in the Muynoq District of the Republic of Karakalpakstan. Field surveys were conducted during the 2022–2023 vegetation seasons, covering both low-water and high-water periods. The equipment and software used in this study are summarised in Table 1.

Table 1.

Field equipment and software used in the study

#	Equipment / Software	Model	Purpose	Accuracy / Spec.
1	GPS navigator	Garmin eTrex 32x	Coordinate determination of survey points	±3 m horizontal (WGS-84)
2	Optical level	Leica NA332	Absolute elevation measurement along profiles	±2.0 mm/km double-run
3	Electronic theodolite	VEGA TEO-20B/5B	Angular and elevation control measurements	20″ angular accuracy
4	Sounding rod	Standard graduated	Manual bathymetric depth measurement	±0.01 m
5	Plankton net	No. 76	Zooplankton sample collection	Mesh 64 µm
6	Light microscope	Micmed-6	Species identification and enumeration	×100–400

#	Equipment / Software	Model	Purpose	Accuracy / Spec.
7	Counting chamber	Bogorov chamber	Quantitative zooplankton counting	Volume 1 ml
8	GIS software	ArcGIS 10.8 (ESRI)	DEM, isobath analysis, morphometric calc.	TIN/IDW interpolation [6]
9	Water balance model	Visual C# (.NET)	Differential water balance computation	Δt = 1 month
10	Statistics	MS Excel 2019	Hydrological statistics (Cv, Cs)	Kritsky–Menkel distribution

2.2. Bathymetric survey and morphometric analysis

Prior to field surveys, each water body was divided into cross-sectional profiles oriented perpendicular to the main longitudinal axis. For the Mezhdurechye Reservoir, 8 profiles were established at approximately 500 m intervals; for Muynoq Bay, 7 profiles at 600 m intervals; and for Balikchi Bay, 6 profiles at 400 m intervals. Profile endpoints were marked and their coordinates recorded using the Garmin eTrex 32x GPS navigator. Along each profile, depth measurements were taken at 50–100 m intervals using a graduated sounding rod, yielding (x, y, depth) triplets for the entire water body. In total, 312 sounding points were collected: 128 for Mezhdurechye, 104 for Muynoq Bay, and 80 for Balikchi Bay.

Absolute elevation of the water surface was measured at each water body using the Leica NA332 optical level, referenced to the Baltic Height System (BHS-1977). All depth readings were converted to absolute bed elevation: $Z_{nea} = Z_{surface} - d$, where d is the measured water depth. All (x, y, Z_{nea}) data were imported into ArcGIS 10.8 and a Digital Elevation Model (DEM) was constructed using the Triangulated Irregular Network (TIN) method at 10 m × 10 m resolution [7, 8]. Isobath contour lines were generated at 0.5 m intervals, and area–elevation and volume–elevation curves were derived using the Surface Volume tool in ArcGIS Spatial Analyst [9].

Volume was computed by the isobath (prismatoid) method:

$$V = \left[\frac{(W_i + W_{i+1})}{2}\right] \bullet h_i; \tag{1}$$

where V is the reservoir volume (m³), W_i is the area enclosed by isobath i (m²), and h_i is the elevation difference between adjacent isobaths (m). Mean depth was derived as $H_{mean} = V / W$.

2.3. Hydrological data analysis

Multi-year discharge data (1965–2022) were obtained from the Kyzyldzhar hydrometric station archives [10]. Statistical parameters — long-term mean, coefficient of variation (Cv), and asymmetry coefficient (Cs) — were calculated by standard methods, and flow provision curves (3 %, 50 %, 96 %) were constructed using the Kritsky–Menkel distribution.

2.4. Water balance model

A differential water balance model was developed in Visual C#, based on a system of three coupled differential equations for each water body (Mezhdurechye — *i*=1, Muynoq Bay — *i*=2, Balikchi Bay — *i*=3):

$$\frac{dV_i}{dt} = Q_{in,i}(t) - Q_{out,i}(t) - E_i(t) - F_i(t), \quad i = 1, 2, 3; \tag{2}$$

where:

- V_i — water volume of the i-th water body (m³);
- $Q_{in,i}(t)$ — inflow discharge to the i-th water body (m³/month);
- $Q_{out,i}(t)$ — outflow discharge from the i-th water body (m³/month);
- $E_i(t)$ — evaporation losses from the water surface of the i-th water body (m³/month);
- $F_i(t)$ — filtration (seepage) losses from the i-th water body (m³/month).

The three equations are coupled through the shared allocation of the total Amudarya discharge arriving at the Kyzyldzhar station among the canal network (Glavmyaso, Marinkinuzak and others) that supplies the three basins. The model was solved using the finite-difference (Euler forward) method with a monthly time step ($\Delta t = 1$ month). Initial conditions were set as field-measured water volumes at the start of each characteristic year (Table 2). Canal transmission losses were set at 25% of inflow, based on long-term observational data [1]. Monthly evaporation losses were computed as $E(k) = e(k) \cdot W(k)$, where $e(k)$ is the monthly evaporation layer (mm/month) from the Muynoq meteorological station, and $W(k)$ is the current water surface area. Filtration losses were estimated using Darcy's law with a specific seepage rate $f = 0.5$ mm/day [2, 11].

Table 2.

Initial conditions for water balance modelling (field-measured volumes, mln. m³)

Characteristic year	Water availability	Flow provision (%)	V_0 Mezhdurechye	V_0 Muynoq Bay	V_0 Balikchi Bay
2010	Wet	3%	18.4	24.7	6.3
2019	Average	50%	12.6	17.2	4.1
2001	Dry	96%	5.8	8.4	1.7

Model calibration was performed against the average year (2019) by minimising RMSE between computed and observed monthly volumes. The calibrated canal diversion coefficient was $\alpha = 0.68$ and seepage rate $f = 0.5$ mm/day. The model was then validated independently against 2010 and 2001 data (Table 3).

Table 3.

Model validation metrics by water body

Metric	Mezhdurechye	Muynoq Bay	Balikchi Bay
RMSE (mln. m³)	0.74	1.12	0.38
MAE (mln. m³)	0.61	0.94	0.31
Nash–Sutcliffe Efficiency (NSE)	0.87	0.83	0.89

NSE values of 0.83–0.89 indicate good to very good model performance, confirming reliable reproduction of seasonal water storage dynamics [11, 12].

2.5. Hydrobiological sampling

Zooplankton sampling was carried out at fixed stations during the 2022–2023 field seasons using a plankton net No. 76 (mesh 64 µm). A total of 32 samples were collected and fixed with 4 % formaldehyde. Laboratory analysis was performed under a Micmed-6 light microscope using a Bogorov counting chamber. Taxonomic identification followed standard keys for Rotifera, Cladocera, and Copepoda [13, 14]. Abundance (ind./m³) and biomass (mg/m³) were calculated per station and water body.

3. Results and discussion

3.1. Morphometric characteristics: field measurements vs. design values

GPS field surveys and ArcGIS 10.8 isobath analysis yielded current morphometric parameters for all three water bodies. Table 4 compares these against 1975 design values from Uzgiprovodkhoz [15].

Table 4.

Comparison of design and field-measured morphometric parameters (2022–2023)

Parameter	Design (1975)	Current (2022–23)	Change (%)
MEZHDURECHYE RESERVOIR			
Surface area (ha) at H = 57.0 m	21 400	16 411	−23.4%
Total volume (mln. m³)	230.0	199.9	−13.1%
Maximum depth (m)	6–7	5–6	∼−17%
Mean depth (m)	—	1.74	—
MUYNOQ BAY			
Surface area (ha)	15 034	12 529	−16.7%
Total volume (mln. m³)	210.0	184.97	−11.9%
Maximum depth (m)	4.2	4.0–4.2	−0.5%
Mean depth (m)	—	1.48	—
BALIKCHI (SARBAS) BAY			
Surface area (ha)	7 304	6 243	−14.5%
Total volume (mln. m³)	151.4	124.91	−17.5%
Maximum depth (m)	4.0	3.5–4.0	−3.5%
Mean depth (m)	—	2.0	—

Cross-validation of ArcGIS-derived mean depths against field sounding means confirmed the reliability of the spatial analysis: relative errors did not exceed 2.7 % for any water body [8]. The greatest proportional volume loss was recorded at Balikchi Bay (−17.5 %), reflecting its position at the distal end of the delta supply system. The area–elevation and volume–elevation (bathymetric) curves derived for the Mezhdurechye Reservoir and Muynoq Bay are shown in Figure 1; these curves served as the primary tool for extracting morphometric parameters and as direct input to the water balance model.

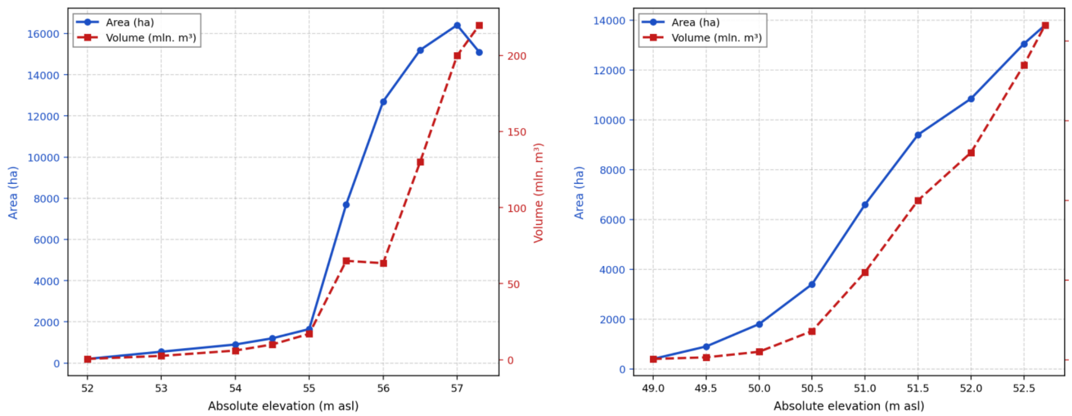

Figure 1. Bathymetric area–elevation and volume–elevation curves of the Mezhdurechye Reservoir and Muynoq Bay (ArcGIS 10.8, field surveys 2022–2023)

3.2. Long-term Amudarya discharge trends (1965–2022)

Analysis of 58-year discharge records from the Kyzyldzhar hydrometric station reveals a sharp declining trend (Figure 2). The maximum monthly mean discharge in 1969 was 3,530 m³/s; by 2001 it had fallen to 2.1 m³/s. Long-term mean discharge: 177.48 m³/s. Flow provision parameters: 3 % provision — 714.1 m³/s (1980); 50 % provision — 116.9 m³/s (2000); 96 % provision — 2.83 m³/s (2021). The coefficient of variation $Cv = 1.08$ and asymmetry coefficient $Cs = 1.79$ confirm extreme flow regime instability and high risk of prolonged drought [7, 16]. This sharp declining trend beginning in the mid-1990s is consistent with satellite-based findings on delta lake shrinkage [3, 17].

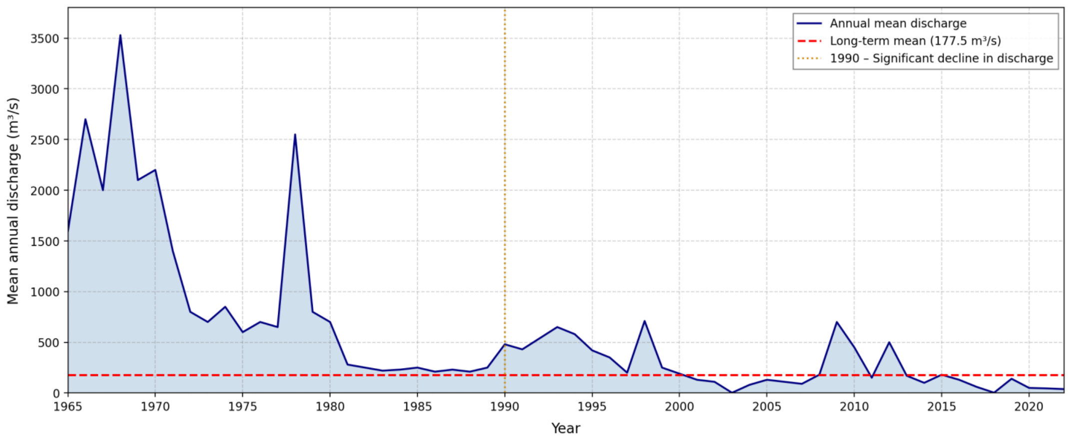

Figure 2. Dynamics of annual mean discharge of the Amudarya River at the Kyzyldzhar hydrometric station (1965–2022). Dashed line — long-term mean (177.48 m³/s)

3.3. Water balance modelling results

Water balance modelling results for the three characteristic years are presented in Table 5 [12, 18].

Table 5.

Water balance of the delta system in different hydrological years (modelling results)

Parameter	Wet year (2010)	Average year (2019)	Dry year (2001)
Total inflow (mln. m³)	16 817.7	1 674.4	100.89
Canal losses (mln. m³)	4 204.4	418.6	25.22
Total evaporation (mln. m³)	14.50	11.44	4.95

Parameter	Wet year (2010)	Average year (2019)	Dry year (2001)
Filtration (mln. m³)	1.30	1.14	0.17
Loss fraction (%)	25.0%	25.0%	25.0%
Water reaching basins (mln. m³)	~12 600	~1 244	~70.5

In a dry year (2001) total water reaching the delta basins was only 100.89 mln. m³ — 166 times less than in the wet year (2010, 16 817.7 mln. m³). Model NSE = 0.83–0.89 confirms reliable performance across all validation years.

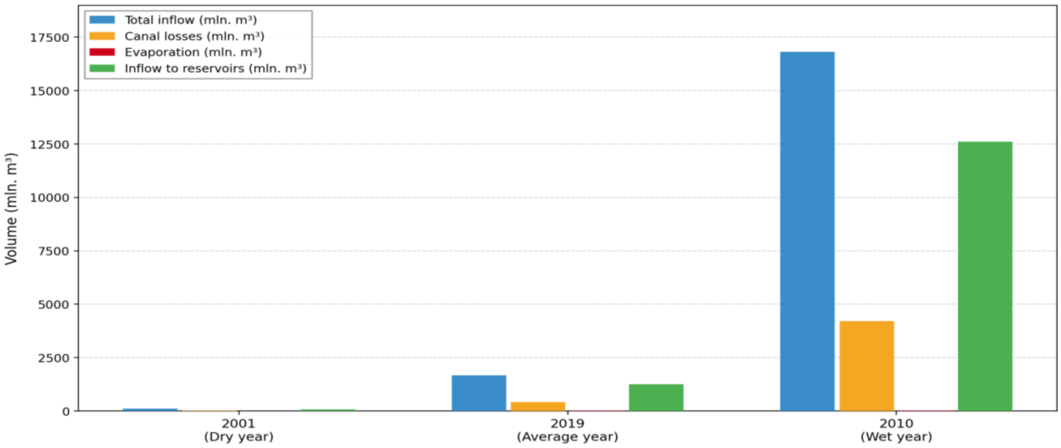

Figure 3. Water balance components of the Amudarya Delta system under wet (2010), average (2019), and dry (2001) hydrological years (GIS-based modelling, Visual C#)

3.4. Hydrobiological results and statistical analysis

A total of 32 zooplankton samples were collected: 12 from Mezhdurechye Reservoir (4 stations × 3 dates), 12 from Muynoq Bay (4 stations × 3 dates), and 8 from Balikchi Bay (4 stations × 2 dates). Twenty-seven species were identified: 15 Rotifera (55.6 %), 6 Cladocera (22.2 %), 6 Copepoda (22.2 %). This is markedly fewer than the 36 species recorded in 1968–1983 [13, 14], indicating long-term ecological impoverishment.

Table 6.

Zooplankton species composition by water body (2022–2023)

Taxonomic group	Total	Mezhdurechye	Muynoq Bay	Balikchi Bay
Rotifera	15	13	11	8
Cladocera	6	5	4	3
Copepoda	6	6	5	4
Total species	27	24	20	15

Table 7.

Mean zooplankton abundance and biomass by water body (mean ± SD)

Water body	n	Abundance (ind./m³)	SD	Biomass (mg/m³)	SD	Dominant group
Mezhdurechye	12	4 820	1 340	312.4	87.6	Rotifera (61%)
Muynoq Bay	12	3 150	980	198.7	64.3	Rotifera (58%)
Balikchi Bay	8	1 740	620	94.3	31.8	Copepoda (47%)

Table 8.

Seasonal dynamics of zooplankton abundance (ind./m³, mean ± SD)

Sampling period	Mezhdurechye	Muynoq Bay	Balikchi Bay
Spring (Apr–May)	6 410 ± 1 120	4 380 ± 890	2 290 ± 540
Summer (Jul–Aug)	3 640 ± 980	2 110 ± 670	1 020 ± 310
Autumn (Sep–Oct)	4 410 ± 1 050	2 960 ± 720	1 910 ± 480

Summer values averaged 43–55 % below spring peaks, directly linked to seasonal minimum Amudarya inflow documented at Kyzyldzhar station. A positive relationship was found between total volume and all biological indicators: Pearson r = 0.97–0.99 across the three water bodies [19], confirming that hydrological status is the primary driver of zooplankton productivity in the delta [20].

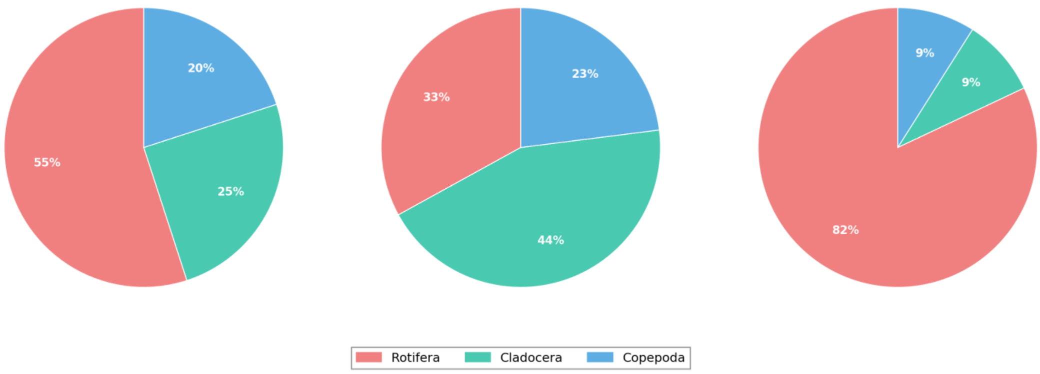

Figure 4. Taxonomic composition of zooplankton communities in the three study water bodies of the lower Amudarya (field surveys 2022–2023). Proportions of Rotifera, Cladocera, and Copepoda

4. Conclusions

1. GIS-based field surveys (Garmin eTrex 32x, Leica NA332, VEGA TEO-20B/5B) combined with TIN-based DEM construction and isobath-method volume computation in ArcGIS 10.8 [6, 8] showed that current morphometric parameters of the three water bodies deviate significantly from 1975 design values [15]: Mezhdurechye Reservoir −13.1 % volume, Muynoq Bay −11.9 %, Balikchi Bay −17.5 %. Cross-validation confirmed ArcGIS accuracy to within 2.7 %. Recommendation: systematic bathymetric re-surveys at 5-year intervals are required to monitor siltation and inform dredging operations.

2. Analysis of 58-year discharge records at the Kyzyldzhar station [10] yielded Cv = 1.08, Cs = 1.79, confirming extreme flow instability. Dry-year discharge (2.83 m³/s in 2021) was 252 times lower than wet-year discharge (714.1 m³/s in 1980) [2, 11]. Recommendation: a minimum ecological flow of ≥50 m³/s at the Kyzyldzhar station must be established as a regulatory threshold.

3. The Visual C# differential water balance model (3 coupled equations, Δt = 1 month, NSE = 0.83–0.89) [11, 12] demonstrated that water reaching the delta in a dry year (2001, 100.89 mln. m³) was 166 times less than in a wet year (2010). Recommendation: restoring design capacities of the Glavmyaso canal (44 m³/s) and Marinkinuzak canal (50 m³/s) would increase effective inflow by an estimated 25–30 % [21, 22].

4. Zooplankton surveys (32 samples, 27 species across 3 water bodies) confirmed direct biological response to hydrological decline: species richness fell from 36 (1968–1983) to 27 (2022–2023), a 25 % reduction [13, 14]. Abundance declined from 4 820 ind./m³ (Mezhdurechye) to 1 740 ind./m³ (Balikchi), Pearson r = 0.97–0.99 [19]. Recommendation: minimum inflow to maintain mineralisation below 2.0 g/l must be incorporated into water allocation plans.

5. The integrated GIS–hydrological framework developed in this study provides a replicable tool for monitoring and managing water resources in degraded arid-region delta systems [7, 9], consistent with the national policy framework for the Aral Sea region [23] and current scientific consensus on restoration potential of the southern Aral Sea basin [4, 5]. The framework can serve as an operational tool for annual water allocation planning by water management authorities of the Republic of Karakalpakstan [16, 17], while accounting for the influence of upstream anthropogenic water use and climatic change on future streamflow composition in the Amu Darya Basin [24]. Recommendation: the integrated GIS–hydrological assessment framework should be adopted as a standard monitoring and planning tool by the relevant water management authorities, with annual updates of morphometric and hydrological data.

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Methodological approach to risk management in IT projects through identification, assessment and minimization of project deviations

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Методический подход к управлению рисками в IT-проектах путем выявления, оценки и минимизации проектных отклонений

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Abstract

The article examines the problem of risk management in IT projects based on the identification, assessment and minimization of project deviations. The relevance of the study is determined by the growing uncertainty in the development of software products, digital services and corporate information systems. The purpose of the study is to develop and substantiate a methodological approach to IT project risk management based on the early identification, quantitative assessment, and minimization of project deviations. A methodological approach is proposed in which risk assessment is based on measurable deviations of the actual project state from planned, target, or acceptable values. The classification of project deviations is substantiated, the causes of their occurrence are revealed, and a methodology for early diagnosis and integrated risk assessment is proposed. Special attention is paid to the use of AI tools for anomaly detection, prediction of critical deviations and preparation of response options. The practical significance of the study lies in the possibility of applying the proposed approach in IT project management, project offices and development teams.The methodological novelty of the study lies in linking risk management with a system of regular monitoring of project data, including the backlog, sprint backlog, issue tracker, CI/CD, test reports, and team performance indicators. The proposed model

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makes it possible not only to record risk events that have already occurred, but also to identify early signals of their escalation, rank deviations by probability, impact, and response urgency, and develop a well-founded mitigation plan. The proposed approach enhances the transparency of managerial decision-making and can serve as a basis for standardizing risk control procedures in IT teams.

Аннотация

В статье рассматривается проблема управления рисками в IT-проектах на основе выявления, оценки и минимизации проектных отклонений. Актуальность исследования определяется повышением неопределенности в сфере разработки программных продуктов, цифровых сервисов и корпоративных информационных систем. Цель исследования состоит в разработке и обосновании методического подхода к управлению рисками IT-проектов на основе раннего выявления, количественной оценки и минимизации проектных отклонений. В качестве основы предложен методический подход, при котором риск рассматривается через измеримое отклонение фактического состояния проекта от планового, целевого или допустимого уровня. Обоснована классификация проектных отклонений, раскрыты причины их возникновения, предложена методика ранней диагностики и интегральная оценка риска. Отдельное внимание уделено применению AI-инструментов для выявления аномалий, прогнозирования критических отклонений и подготовки вариантов мер реагирования. Практическая значимость исследования состоит в возможности применения предложенного подхода в управлении IT-проектами, проектных офисах и командах разработки. Методическая новизна работы заключается в увязке риск-менеджмента с системой регулярного мониторинга проектных данных: backlog, sprint backlog, issue tracker, CI/CD, отчетов о тестировании и показателей командной производительности. Предложенная модель позволяет фиксировать наступившие рисковые события, а также выявлять ранние сигналы их эскалации, ранжировать отклонения по вероятности, влиянию и срочности реагирования, а также формировать обоснованный mitigation plan. Предложенный подход способствует повышению прозрачности управленческих решений и может быть использован как основа для стандартизации процедур контроля рисков в IT-командах.

Keywords: IT project, risk management, project deviations, project management, AI, machine learning, mitigation plan.

Ключевые слова: IT-проект, управление рисками, проектные отклонения, проектное управление, AI, machine learning, mitigation plan.

Introduction

Risk management in IT projects is one of the most important areas of project management. The development of digital products is characterized by a high degree of uncertainty regarding final requirements, the need for rapid adaptation to changing requirements, and the continuous evolution of technologies, while also being highly dependent on team competencies, budget constraints, and project schedules. As a result, IT projects are exposed to elevated risks associated with changing requirements, external integrations, contractor performance, information security requirements, and stakeholder expectations. A distinctive feature of IT projects is the delayed manifestation of risk events. The delayed and cumulative effects of project risks remain one of the major challenges in IT project management, the effective resolution of which requires the application of scientifically grounded approaches [1]. Classical software risk management also emphasizes proactive identification and elimination of risk items before they become sources of project failure [2].

The aim of the study is to develop a methodological approach to risk management in IT projects through the identification, assessment, and minimization of project deviations.

Research methodology

The study is based on the analysis of scientific publications on software project risk management, the identification of risk factors, the diagnosis of project deviations, the application of Scrum artifacts, and the use of machine learning in project risk management.

The methodological procedure combines the classification of observable project deviations, their early diagnosis based on operational project data, identification of the underlying risk factor, integrated risk scoring, selection of a response measure, and subsequent reassessment. In the proposed approach, a project deviation is not equated with risk itself. It is treated as an observable early signal indicating that a risk may materialize or escalate. This distinction makes it possible to move from the identification of abstract risk factors to the monitoring of measurable changes in the actual state of an IT project.

For the quantitative prioritization of identified deviations, an integrated risk score is proposed:

$$R = P \cdot I \cdot U,$$

where R is the integrated risk score associated with the identified project deviation; P is the estimated probability that the detected deviation will lead to further risk escalation or an adverse project event; I is the normalized degree of impact on project objectives; and U is the urgency of managerial response. All parameters take values from 0 to 1.

The value of P can be determined from historical project data, the observed frequency of similar deviations, or predictive estimates generated from previous project cases. The value of I reflects the expected effect of the deviation on schedule, cost, scope, quality, or other critical project objectives. The value of U characterizes the time sensitivity of the deviation and increases as the admissible period for managerial response decreases.

For operational interpretation, the following working intervals are used: $R < 0.125$ – low risk; $0.125 \le R < 0.343$ – moderate risk; $0.343 \le R < 0.512$ – high risk; and $R \ge 0.512$ – critical risk. The threshold values correspond to the simultaneous achievement of benchmark levels of 0.5, 0.7, and 0.8 by the three assessment parameters ($0.5^3 = 0.125$; $0.7^3 = 0.343$; $0.8^3 = 0.512$). The thresholds may subsequently be calibrated using historical data from a specific organization or project portfolio.

All parameters are assessed on a scale from 0 to 1. A value close to 1 indicates a high level of the corresponding parameter. The assessment also incorporates the response urgency parameter, which makes it possible to account for the time sensitivity of the deviation.

Results and discussion

Risks in IT projects are traditionally characterized by the simultaneous presence of organizational, technical, managerial, and user-related factors. Risks in IT projects arise as a result of changing requirements, planning errors, reduced team performance, an increasing number of defects, limited customer involvement, delays in approvals, integration issues, and insufficient project data. A project deviation can serve as one of the earliest observable signals of risk materialization or escalation. By its nature, risk reflects the probability of an adverse outcome, whereas a deviation captures an existing discrepancy between the planned and the actual project state. Within the context of IT project management, it is advisable to focus on the analysis of project deviations, as they are measurable and can be incorporated into a project monitoring system.

Accordingly, the proposed approach does not replace conventional risk identification with deviation analysis. Rather, it introduces project deviation as an intermediate observable element between a risk factor and a possible adverse project outcome. The resulting relationship can be represented as follows: 1) risk factor; 2) measurable project deviation; 3) risk escalation; 4) adverse project outcome. This makes it possible to identify a developing risk before its consequences become fully manifested in project schedule, cost, scope, or quality indicators.

Unlike classifications focused primarily on sources and categories of software project risks [3; 4; 10], the proposed classification describes the detected deviation simultaneously from several managerial perspectives: the affected project area, the source of the deviation, the project stage at which it occurs, the indicator through which it can be detected, and the urgency of response. Therefore, the classification presented in Figure 1 performs not only a descriptive function but also supports the subsequent selection of diagnostic indicators and response measures.

Risk factors should be considered within the following groups: requirements, customer, team, technologies, planning, external environment, and change management [3]. In the context of IT projects, different groups of risk factors are often interrelated. The main types of project deviations are presented in Figure 1.

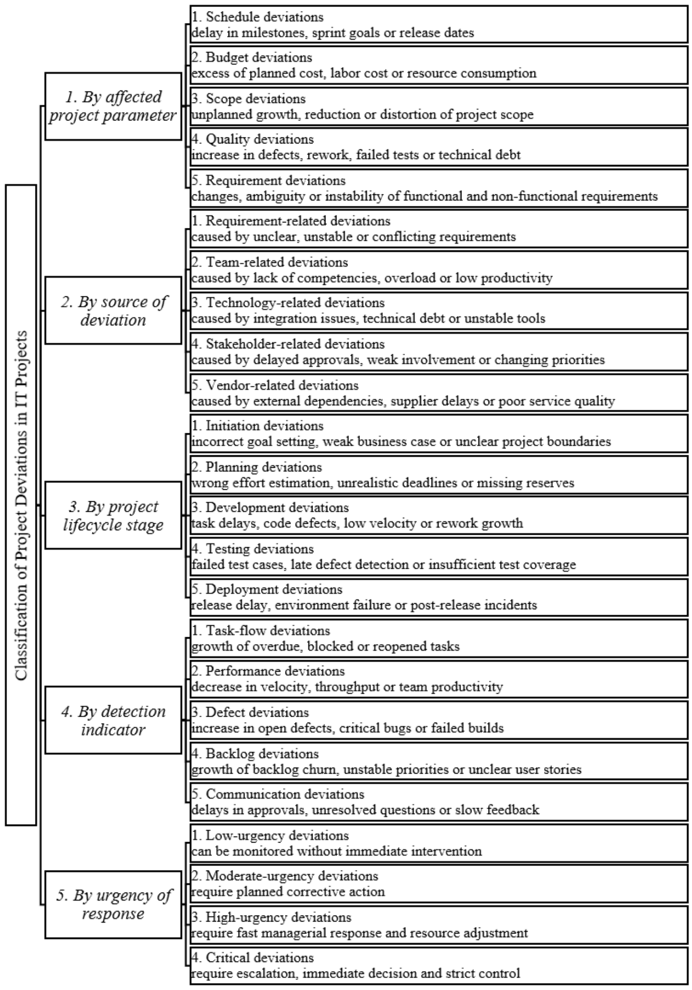

Figure 1. Classification of project deviations in IT projects

The determinants of risk occurrence in IT projects can be divided into several groups:

1. requirements-related determinants, including poorly defined requirements, frequent backlog changes, the absence of acceptance criteria, and conflicting customer expectations;

2. team-related determinants, including competency gaps, team member overload, ineffective role distribution, and a low task completion rate;

3. planning-related determinants, including underestimated effort estimates, insufficient task decomposition, the absence of time reserves, and inadequate assessment of external dependencies;

4. technology-related determinants, including complex integrations, increasing technical debt, an unstable development environment, CI/CD issues, late defect detection, and insufficient test coverage;

5. customer- and external stakeholder-related determinants, including delays in approvals, changing priorities, dependence on contractors, and a gap between business expectations and the team's capabilities.

Previous studies identify user involvement, management support, requirements management, team experience, and change control among the significant factors affecting software project risks [4]. Risks in IT projects rarely arise from a single source; rather, they more often emerge at the intersection of organizational decisions, technical conditions, and the quality of communication. The impact of risks is reflected in the deterioration of project performance, as they may lead to schedule delays, budget overruns, reduced quality, loss of functionality, an increase in the number of defects, and reduced team effectiveness. Moreover, different dimensions of risk affect project schedule, cost, and quality in different ways [5]. Therefore, risk assessment should also take into account the magnitude of a risk's impact on project outcomes.

The traditional risk matrix, based on probability and impact, is useful for the initial assessment of risks. However, IT projects often require the introduction of an additional parameter-response urgency. This parameter reflects how quickly a decision must be made and is particularly important when managing sprints, release cycles, integration dependencies, and critical defects. General project management and risk management standards also emphasize the need to integrate risk-related decisions into planning, monitoring, response selection and stakeholder communication [6; 7].

Based on the above, the methodology for the early diagnosis of project deviations includes four interrelated stages:

1. Data collection. Project information is obtained from the backlog, sprint backlog, issue tracker, burndown chart, testing reports, CI/CD systems, task statuses, defect logs, overtime records, requirement change history, and data on external dependencies. At this stage, the objective is to create a unified set of operational data suitable for subsequent diagnostic analysis.

2. Diagnostic analysis. The collected data are used to calculate indicators reflecting schedule deviation, the proportion of overdue and blocked tasks, changes in velocity, growth in open defects, reopened issues, backlog churn, deviation of actual effort from estimated effort, approval delays, and the proportion of tasks without acceptance criteria. A deviation is recorded when the actual value exceeds an established project threshold or demonstrates a persistent negative trend.

3. Risk evaluation. The root cause and the corresponding risk factor are identified for each detected deviation. The values of P, I, and U are then estimated, after which the integrated risk score $R = P \cdot I \cdot U$ is calculated and the deviation is assigned to a low, moderate, high, or critical risk category.

4. Response preparation. The calculated value of R, together with the type and root cause of the deviation, is used to determine the required managerial response. Low-risk deviations remain under monitoring; moderate risks require planned corrective actions; high risks require a formal mitigation plan; and critical risks require immediate intervention and escalation.

Modern software risk management requires a reconsideration of the role of risk management within a project, as risks should be analyzed throughout the entire project lifecycle rather than only during the planning phase [8; 9]. Early diagnosis of project deviations thus becomes a continuous management process (Figure 2).

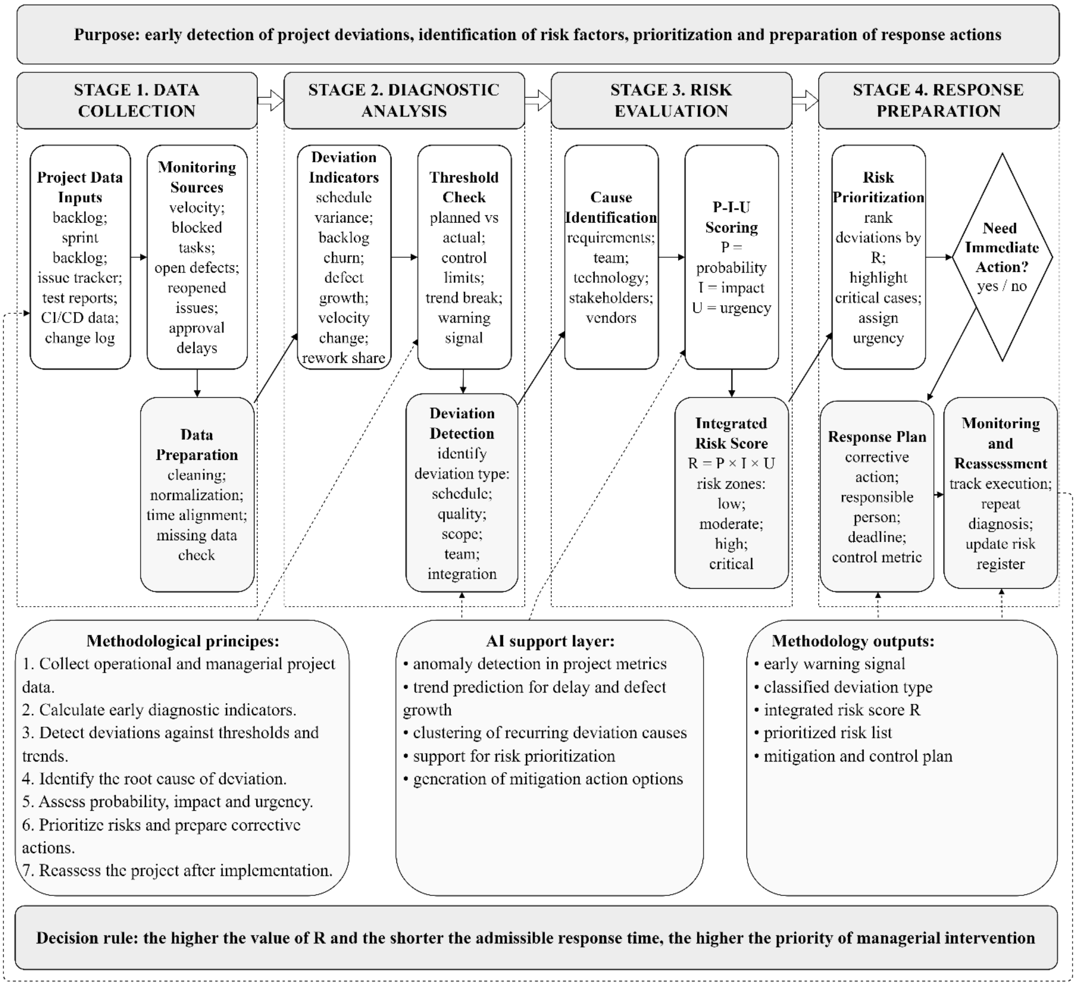

Figure 2. Methodology for the early diagnosis of project deviations

The proposed sequence extends the conventional probability–impact approach by introducing two additional elements. First, risk assessment is initiated by an observable deviation detected in current project data rather than solely by periodic expert identification of potential risks. Second, the inclusion of response urgency U distinguishes situations with similar probability and impact but different admissible response times. This distinction is particularly relevant to IT projects, where a blocked deployment pipeline, a critical security defect, or an unresolved integration dependency may require substantially faster intervention than another risk with a comparable expected impact. Thus, the proposed score does not replace the traditional probability–impact assessment reflected in project and risk management standards [6; 7], but operationalizes it for continuous monitoring of IT projects.

Within the proposed methodology, AI tools can support four analytical operations associated with the processing and interpretation of project data:

1. at the data collection stage, AI helps process information from the issue tracker, backlog, testing reports, and task statuses.

2. at the deviation detection stage, AI tools can identify anomalies in task dynamics, team velocity, the number of defects, and the frequency of requirements changes.

3. at the root cause analysis stage, clustering techniques can be applied to identify recurring problems.

4. at the risk assessment stage, AI can support the prediction of whether a deviation is likely to escalate to a high- or critical-risk level.

Within the proposed methodology, AI is therefore treated as a supporting analytical layer rather than as an independent risk assessment dimension. Its principal functions are anomaly detection in operational project metrics, identification of recurring deviation patterns, estimation of escalation probability, and analytical support for the selection of response options. The final values of I and U, as well as the managerial decision concerning the mitigation measure, remain subject to project management assessment. Thus, AI support influences the quality and speed of risk diagnosis but does not replace the integrated risk score R or managerial responsibility for the final decision.

The risk mitigation model is based on the transition from identifying a project deviation to taking a management action (Figure 3). Once a deviation has been identified, its cause is determined, after which the value of R is calculated and the risk is assigned to a priority category. An appropriate response measure is then selected, such as reducing the probability of occurrence, reducing the impact, decreasing response urgency, extending the schedule, reallocating resources, refining requirements, conducting additional testing, performing a technical review, carrying out a security review, or escalating the issue.

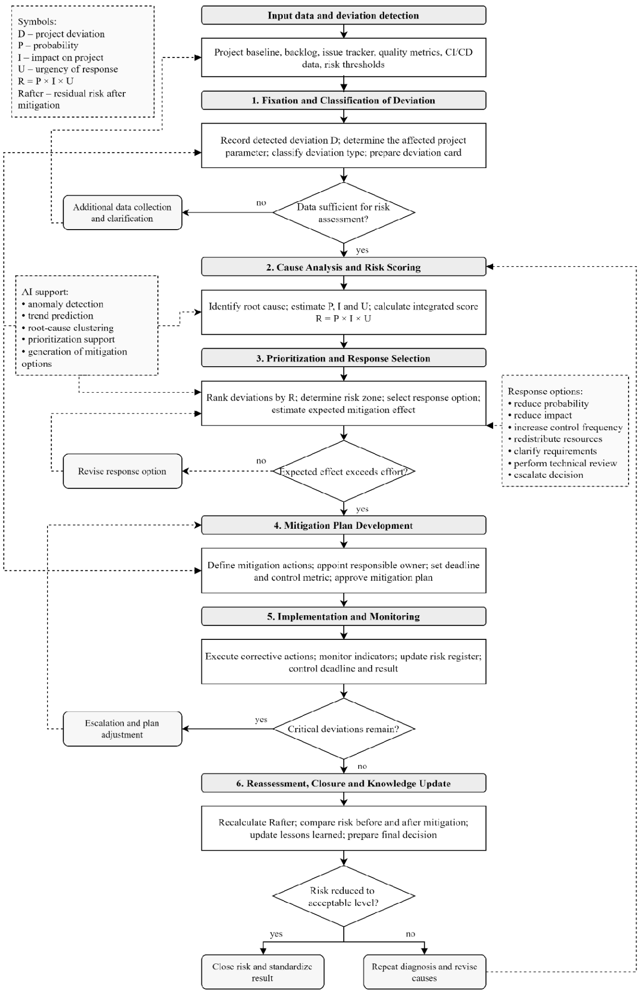

Figure 3. Risk mitigation and project deviation management model

To demonstrate the application of the proposed methodological approach, an illustrative reassessment of eight groups of project deviations was performed (Figure 4). The assessment compares the integrated risk score R before and after the implementation of mitigation measures.

The purpose of this comparison is to demonstrate how the proposed indicator can be used not only for initial risk prioritization but also for subsequent control of the effectiveness of managerial intervention. The difference between the initial and reassessed values is determined as follows:

$$\Delta R = R_{before} - R_{after}.$$

A positive value of ΔRindicates a reduction in the integrated risk score after mitigation. The relative effectiveness of mitigation can additionally be determined as:

$$E_R = \frac{R_{before} - R_{after}}{R_{before}} \times 100\%.$$

This indicator makes it possible to compare the effectiveness of risk response measures across deviation groups with different initial levels of R.

Deviation group	R before	R after	Risk reduction
Requirement deviations	0,574	0,312	0,261
Schedule deviations	0,476	0,276	0,200
Quality deviations	0,390	0,221	0,169
Team productivity deviations	0,384	0,228	0,156
Integration deviations	0,351	0,208	0,143
Security deviations	0,365	0,194	0,170
Vendor dependency deviations	0,228	0,139	0,088
Communication deviations	0,250	0,139	0,112

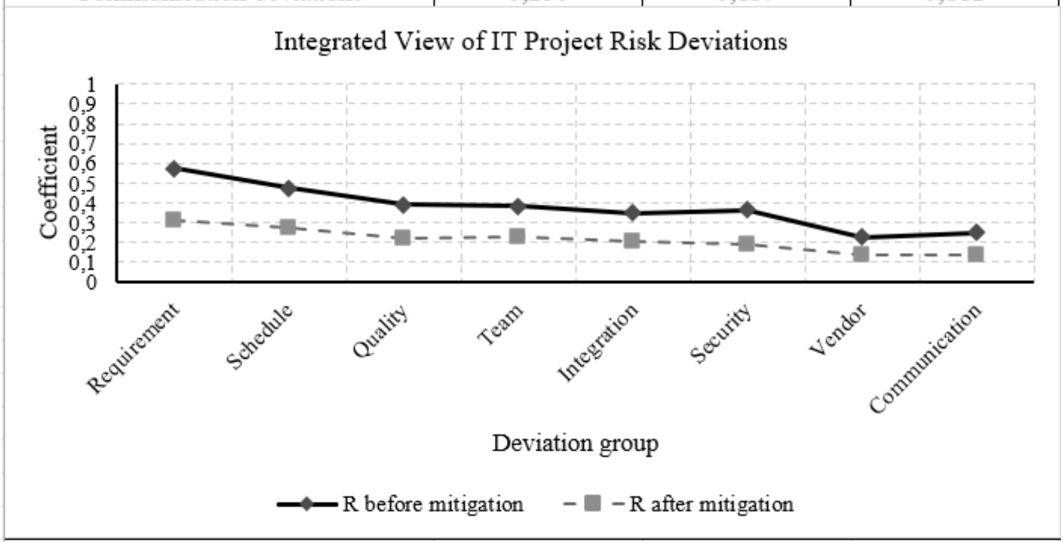

Figure 4. Changes in integrated risk scores before and after mitigation measures

Source: prepared by the author.

The results presented in Figure 4 demonstrate a decrease in the integrated risk score for all eight groups of project deviations. The average value of R decreased from 0.377 before mitigation to 0.215 after mitigation. The average relative reduction amounted to approximately 42.8 %, indicating that the application of corrective and mitigation measures produced a consistent decrease in the assessed level of project risk across the analyzed deviation groups.

The largest absolute reduction was observed for requirement deviations, for which R decreased from 0.574 to 0.312 ($\Delta R = 0.262$). According to the proposed scale, this corresponds to a transition from the critical to the moderate risk category. The result indicates that deviations related to unstable or conflicting requirements can be substantially reduced when the response is directed toward requirement clarification, backlog stabilization, specification of acceptance criteria, and coordination with stakeholders.

A substantial reduction was also recorded for security deviations, where R decreased from 0.365 to 0.194, corresponding to a relative reduction of approximately 46.8 %. Schedule, quality, team productivity, and integration deviations initially belonged to the high-risk category and moved to the moderate-risk category after mitigation. This result demonstrates the practical role of repeated risk scoring: the methodology makes it possible to determine whether the implemented measures have changed the priority of a detected deviation rather than merely documenting that a corrective action has been performed.

Vendor dependency deviations demonstrated the smallest absolute reduction ($\Delta R = 0.089$) and remained within the moderate-risk category. This result may be explained by the limited ability of an internal project team to directly influence external suppliers and dependencies. In such cases, mitigation measures can reduce the consequences and improve response preparedness but may have a weaker effect on the underlying probability of the risk event.

The comparison therefore indicates that the effectiveness of mitigation depends on the controllability of the underlying risk factor. Deviations caused by internal project processes, including requirements management, quality control, scheduling, and team coordination, are more directly affected by managerial intervention. Risks associated with external dependencies may require contractual, organizational, or escalation mechanisms beyond the boundaries of the project team. This distinction should be considered when interpreting changes in R and selecting subsequent response measures.

The obtained results also clarify the methodological distinction between the proposed approach and conventional risk factor analysis. Existing studies emphasize the identification of software project risk sources and their classification [3; 4; 10], while proactive risk management focuses on detecting and addressing risk items before they lead to project failure [2]. The proposed methodology develops this direction by introducing measurable project deviations as operational signals connecting risk factors with current project performance. In this respect, continuous monitoring of backlog, issue tracker, testing, and CI/CD data complements lifecycle-oriented approaches to software risk management [8; 9] and provides a quantitative basis for repeated risk reassessment.

At the same time, the proposed approach has limitations. The values of P, I, and U depend on the availability and quality of project data and may require calibration for different organizations and types of IT projects. The threshold values proposed in this study should therefore be considered working reference points rather than universal boundaries. Further research should focus on validating the methodology using longitudinal data from multiple IT projects and comparing expert-based and machine-learning-based estimates of risk escalation probability.

Based on the proposed methodology and the results of repeated risk assessment, the approach can be applied in project offices, product teams, development teams, and digital transformation units. Its practical value lies in linking a risk assessment to a specific measurable project deviation and expressing the required management priority in quantitative terms. This enables the project manager to compare heterogeneous project deviations, identify priority areas for intervention, select appropriate mitigation measures, and subsequently assess whether the implemented actions have reduced the integrated risk score.

Conclusion

The study resulted in the development of a methodological approach to risk management in IT projects based on the transition from the detection of measurable project deviations to risk assessment, prioritization, mitigation, and repeated evaluation. The proposed approach distinguishes between a risk factor, an observable project deviation, and an adverse project outcome, which makes it possible to use current project data as early signals of possible risk escalation.

The methodological contribution of the study consists in combining a multi-criteria classification of project deviations with the integrated risk score $R = P \cdot I \cdot U$, where risk probability and impact are supplemented by the urgency of managerial response. The proposed assessment scale connects the quantitative value of $R$with differentiated management actions ranging from monitoring to immediate escalation. This makes the indicator applicable both to initial risk prioritization and to repeated assessment after mitigation measures have been implemented.

The illustrative application of the approach to eight groups of project deviations demonstrated a decrease in the integrated risk score across all analyzed categories. The average value of R decreased from 0.377 to 0.215, while the average relative reduction was approximately 42.8 %. The largest absolute decrease was observed for requirement deviations, whereas vendor dependency deviations showed a more limited reduction, indicating differences between risks arising from internally controllable project processes and those associated with external dependencies.

AI tools can support the proposed methodology through anomaly detection, identification of recurring deviation patterns, prediction of risk escalation, and preparation of response alternatives. However, AI is considered a supporting analytical layer, while the final assessment of impact and response urgency and the selection of mitigation measures remain the responsibility of the project manager.

The practical significance of the proposed approach lies in its applicability to project offices, software development teams, product teams, and digital transformation units using operational data from backlog management systems, issue trackers, testing environments, and CI/CD pipelines. The principal limitation of the study is the need to calibrate the parameters and threshold values using historical data from specific organizations. Further research should therefore focus on empirical validation of the approach across multiple IT projects and on evaluating the accuracy of AI-supported prediction of project deviation escalation.

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