ISSN 1814-4225 (print)
Radioelectronic and Computer Systems, 2025, no. 4(116) ISSN 2663-2012 (online)

UDC 656.7:331.45:004.8:004.94 **doi: 10.32620/reks.2025.4.01**

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DIGITAL TRANSFORMATION OF THE OCCUPATIONAL HEALTH AND SAFETY MANAGEMENT SYSTEM IN CIVIL AVIATION THROUGH SYNERGETIC INTEGRATION OF DIGITAL TWIN AND AI AGENTS' TECHNOLOGIES

The subject *of this study is the digital transformation of the occupational safety management system in civil aviation. Owing to the country's unique geopolitical position in the centre of Eurasia, the Republic of Kazakhstan's rapid growth in cargo and passenger traffic is associated with increasing employee risks, making it critically necessary to review existing occupational safety management systems. Traditional approaches to occupational safety management, which often focus on reactive elimination of consequences, are insufficiently effective in the context of the dynamic development of a high-tech industry, where every incident has serious economic, reputational, and social repercussions. It is possible to improve occupational safety by applying advanced digital technologies, in particular digital twin and AI agent technologies, which are capable of continuously accumulating, processing, and transmitting vast amounts of data in real time through self-learning, creating a comprehensive picture of an aviation enterprise's entire occupational safety management system's functioning.* ***This study aims*** *to justify the feasibility of modifying the occupational safety management system in civil aviation in the Republic of Kazakhstan by integrating digital twin and AI agent technologies into key functional processes.* ***Results****. The proposed algorithm for the developed AI agent, which is explicitly designed for integration into the occupational safety management systems of aviation enterprises in Kazakhstan, is the key contribution of this study. Its architecture, operating principles, and algorithms for interacting with big data received from digital twins of various elements of the aviation system are described in detail, ranging from the condition of aircraft and ground equipment to the personnel's psychophysiological indicators and the working environment's characteristics. This algorithm enables the AI agent to detect anomalies and build predictive models, signalling potential threats in advance. The results of the AI agent's risk assessment in the civil aviation occupational safety system have been visualised, demonstrating its high efficiency in identifying vulnerabilities, predicting critical situations and forming informed, personalised recommendations for their prevention. The research results demonstrate how proactive monitoring and analysis performed by an AI agent based on digital twin data can significantly reduce the likelihood of injuries and occupational diseases.* ***Conclusions****. The proposed approach to modifying the occupational safety management system at civil aviation enterprises is based on the synergistic integration of digital twins and AI agents, whereby risk management shifts from reactive elimination to preventive modelling and mitigation of potential threats. The creation of an occupational safety management system at the country's aviation enterprises, based on the use of digital twins and AI agents, will significantly increase the competitiveness of civil aviation in the Republic of Kazakhstan on the world market, positioning it as a leader in the application of high-tech solutions for ensuring occupational safety and sustainable development.*

Keywords: *civil aviation; hazardous working conditions; occupational safety; occupational safety management system; injuries; occupational diseases; digital twin; AI agent; digital transformation.*

1. Introduction

1.1. Motivation

The development of civil aviation in the Republic of Kazakhstan is a complex strategic imperative that goes far beyond the sphere of transport. The country's unique geopolitical position and ambitious tasks to diversify the national economy determine it. Situated at the epicentre of the Eurasian continent, Kazakhstan has the fundamental potential to consolidate its status as one of the leading international transit aviation hubs at the intersection of key air corridors linking the largest economic poles of Europe and Asia [1].

Leveraging this geographic advantage is key to Kazakhstan's sustainable economic growth. Increasing cargo and passenger transit volumes generate direct revenues for the aviation industry and catalyse a multiplier effect in related economic sectors, such as logistics, tourism, hospitality, services, and maintenance [2]. This contributes to the national economy's diversification, reducing its dependence on raw materials and attracting significant foreign investment, stimulating the creation of high-tech jobs [3].

Along with the economic aspect, civil aviation development has a critical geopolitical dimension. Strengthening Kazakhstan's transit potential facilitates its integration into global transport systems, strengthens the country's role in international trade and economic relations, and positions it as a strategically important partner on the world stage. Developing a robust aviation infrastructure is vital for realising national interests and enhancing regional stability [4].

However, the growth of aviation activity, particularly the increase in cargo and passenger traffic, is inevitably associated with challenges that necessitate revising existing approaches to industrial safety and labour protection management. The expansion of operational scale, the intensification of work processes, and the complication of technical systems increase the number of workplaces with potentially hazardous conditions, thereby increasing the likelihood of incidents and injuries [5]. In the context of growing requirements for flight and ground handling safety, traditional, often reactive methods of labour protection management are becoming inadequate to the challenges of modern times.

Integrating advanced digital technologies, particularly digital twins (DT) and artificial intelligence (AI) agents, into Kazakhstan's civil aviation occupational safety management system is particularly relevant. Digital twins, virtual representations of physical objects and processes, enable the continuous monitoring of equipment, infrastructure, and even physiological parameters of personnel in real time, thereby providing AI agents with a constant flow of relevant information [6]. This offers unprecedented opportunities for predictive analytics, modelling potentially dangerous scenarios, and identifying hidden risks before they materialise [7].

AI agents can process colossal amounts of data [8] generated by digital twins and other sources, identify complex correlations, and predict the likelihood of incidents caused by technical malfunctions and human factors [9]. They can provide personalised recommendations for preventing fatigue, optimising work schedules, and adjusting personnel actions in critical situations [10].

Only the symbiosis of DT and AI agents will create an adaptive, proactive, and intelligent ecosystem for occupational safety management in civil aviation, a key aspect for minimising risks, increasing operational efficiency, and ensuring unconditional safety in Kazakhstan's rapidly evolving civil aviation sector. It should be recognised that this is not just a technological modernisation but a strategic investment in the sustainable future of the industry and national welfare.

1.2. State of the art

The current stage of digital transformation in high-tech industries, such as civil aviation, is characterised by the active development and convergence of advanced paradigms. The concepts of DT and AI agents occupy a central place among these [11]. The period from 2020 to 2025 was marked by significant progress in their methodologies, architectures, and practical applications. It demonstrated powerful synergistic potential, especially in the proactive management of complex and critical systems, including occupational safety aspects.

Notably, the aerospace industry was one of the first to examine the concept of CG, as evidenced by NASA publications. NASA extended the physical model of the vehicle to include digital components in response to the explosion of the Apollo 13 oxygen tank. This "digital twin" was the first of its kind, enabling continuous data capture to simulate events [12]. However, it was not until 2010 that the paper "Project Roadmap for Modelling, Simulation, Information Technology, and Processing for the National Aeronautics and Space Administration" [13] was published, which conceptualised aerospace CG as a virtual replica that mirrored physical objects, processes or systems.

Since 2020, DT research has shifted from conceptual justification to practical implementation, operationalisation, and optimisation issues. Modern definitions of DTs emphasise their role as dynamic, multidimensional, multi-physical, and multiscale virtual representations of real-world entities, capable of continuous data synchronisation, simulation, and predictive analysis to support informed decision-making [14]. The emphasis is on developing intelligent digital twins that integrate advanced analytics and artificial intelligence elements to enhance their autonomy and predictive capabilities. DT architectural models have evolved to include new layers, such as an AI algorithm layer and a decision/control layer, allowing DTs to reflect reality and actively influence it [15]. Research conducted from 2021 to 2023 is actively focused on creating ontological models to unify data and enhance interoperability among various components of the digital economy. Additionally, it involves developing digital twins for entire systems and ecosystems, a step towards implementing complex management tasks [16]. Key technology trends include advanced sensor networks and Internet of Things devices, where the development of 5G/6G wireless technologies and edge computing enable the faster and more reliable transmission of large amounts of data in real time [17]. Augmented reality (AR) and virtual reality (VR) are increasingly being used to create immersive interaction interfaces with the digital economy [18]. Blockchain technology is also being

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

explored to ensure the integrity, security, and traceability of data were transmitted to the digital economy [19]. In civil aviation, recent studies have investigated the application of digital twins for integrated flight safety management [20], identification of potential in-flight failures [21], the optimisation of aircraft maintenance, repair, and overhaul (MRO) processes [22], prevention of onboard aircraft fires [23], airport operational safety management [24], and the modeling and optimization of operational workflows [25], which has led to the interpretation of the concept of the “digital twin” from different methodological perspectives (Fig. 1).

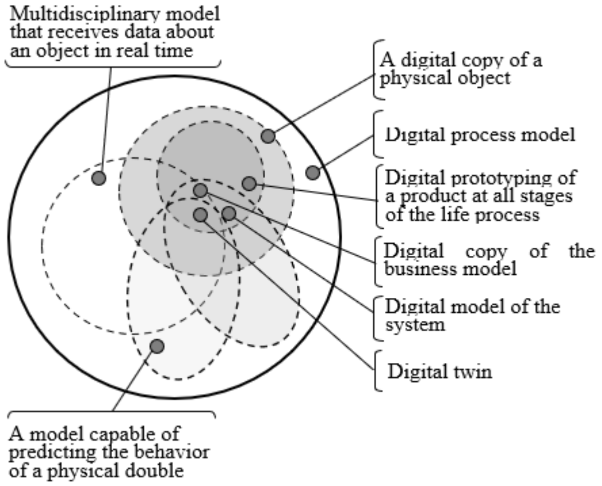

Fig. 1. The boundaries of the DT concept in modern publications [13, 19]

Despite the rapid evolution of the “digital twin” concept and its active implementation in various industries, including civil aviation, a single, generally accepted interpretation of this concept has not yet been established. This observation often raises questions; however, from an academic perspective, such a situation is a normal and even expected consequence of the underlying technologies’ dynamic development [26].

Several factors explain the lack of a strict, universal definition. First, the digital twin is an umbrella term encompassing many technologies, including the IoT, AI, machine learning (ML), cloud computing, augmented and virtual reality (AR/VR), and big data analytics technologies. Each of these technologies is constantly evolving, expanding the functionality and applications of digital twins.

Second, the concept of a “digital twin” is adaptable to the specific needs of various industries and tasks. For example, a digital twin of a mechanical engineering product will differ significantly in its structure and data set from a digital twin of urban infrastructure or an occupational safety management system in aviation. This contextual variability prevents the creation of a comprehensive formulation that is adequate for all cases.

Thus, the "under definition" of the "digital twin" concept is not a disadvantage but reflects its organic, living, and constantly changing nature. This testifies to the concept’s adaptability and potential for further transformation, allowing it to remain relevant and integrate new scientific achievements and technological innovations as they appear [27]. In particular, since 2022, breakthroughs in machine learning, intense learning, and reinforcement learning have significantly enhanced the digital transformation of Kazakhstan’s civil aviation [28]. Therefore, digital twins, which use real-time or historical data input for analysis, have acquired the ability to simulate various scenarios and predict system behaviour, along with machine learning algorithms. The information obtained through such modelling is convenient for posting on dashboards, compiling reports, and visualising them, which enables effective decision-making [29]. However, the capabilities of the digital twin do not fully meet the needs with the development of multi-agent systems, which has become the basis for considering the feasibility of synergistic integration of the digital twin and the AI agent in civil aviation [30].

Modern AI agents strive for autonomy, adaptability, explainability, and collaboration in complex and dynamic environments. Key areas of development include learning agents, where reinforcement learning methods are particularly relevant for creating agents that can make optimal decisions under uncertainty [31]. In response to the need for transparency in deep learning’s “black boxes,” explainable AI methods are being actively developed, enabling AI agents to justify their recommendations and decisions [32]. Research focuses on developing multi-agent systems, where multiple AI agents interact to solve complex distributed problems, which is relevant for safety management, where different aspects of safety can be controlled by specialised agents [33]. Advances in computer vision and natural language processing have enabled AI agents to analyse unstructured data, such as video feeds or text incident reports, to identify hidden patterns and warning signs of danger [34]. The challenges include ensuring the reliability and safety of AI systems, managing bias in data and algorithms, and developing ethical frameworks for autonomous agents [35].

Implementing digital twins and AI agents is now recognised as crucial in developing intelligent control systems for complex technical and socio-technical systems. From 2023 to 2025, this synergy has been the subject of intense research, particularly in the areas of industrial safety and occupational health and safety management. The digital twin is a rich source of relevant, contextualised data for AI agents, providing a virtual environment for training and testing strategies without compromising real systems [36]. In turn, AI agents imbue the digital twin with “intelligence,” allowing it to reflect, analyse, predict, and actively manage its physical counterpart [37]. Current research actively explores how this integration can transform occupational safety and health management, for example, by simulating the airport work environment and analysing personnel data to predict risks and suggest corrective actions [38]. This enables the implementation of the proactive risk management concept.

Thus, the recent literature review convincingly demonstrates significant progress in digital twin and AI agent technologies. Their synergistic integration is a leading direction for creating intelligent, self-adaptive, and explainable control systems, especially in critical areas such as civil aviation's occupational safety management system. This integration presents opportunities for developing a new safety paradigm centred on in-depth predictive analysis, proactive intervention, and continuous improvement, which are essential for enhancing operational reliability and the industry's sustainable development.

1.3. Objectives and tasks

The study focuses on the occupational safety management system of civil aviation enterprises.

The study focuses on the synergistic integration of an AI agent and digital twins within aviation enterprises' occupational safety management system.

This study aims to substantiate the feasibility of implementing a digital transformation of the occupational safety management system in the civil aviation sector through the synergistic integration of digital twin technologies and AI agents into the operational practices of the country's aviation enterprises, ensuring risk prevention and an increased level of industrial safety.

The following tasks were formulated to achieve the goal:

- to study the industry model of the occupational safety management system in Kazakhstan's civil aviation;
- to develop an algorithm for constructing an AI agent explicitly designed for integration into Kazakhstan's occupational safety management system;
- to develop proposals for the synergistic implementation of digital twin technologies and AI agents in the practice of aviation enterprises in the Republic of Kazakhstan.

The article includes an introduction, a literature review, a description of the research methods, the research results, a discussion, and conclusions.

Section 1 describes the study's relevance, purpose, and objectives, as well as a critical analysis of scientific sources and an overview of the problems associated with the digital transformation of the occupational safety management system in civil aviation.

Section 2 describes the research design, methodology, and tools used to achieve the stated research goal.

Section 3 is devoted to the development of an algorithm for constructing an AI agent to manage Kazakhstan's civil aviation's occupational safety system.

Section 4 presents a discussion of the scientific results and their presentation in the form of a methodology, which highlights the study's significance for practical application.

Section 5 concludes the study with a summary of the key findings and prospects for further research.

2. Materials and methods of research

This study's methodology is based on an integrated approach that combines the principles of system analysis, deductive and inductive logic, and methods of mathematical modelling and predictive analytics. This approach enables a comprehensive and in-depth examination of the integration of innovative digital technologies into Kazakhstan's civil aviation occupational safety and health management system, confirming the relevance of the proposed solutions and assessing their potential effectiveness. The initial stage of the study involved a critical review of the current state of occupational safety and health management systems in Kazakhstan's civil aviation to identify key problems. This was followed by the conceptual and design stages, during which an occupational safety and health management model was developed using digital twins and AI agents. Simultaneously, an algorithm for the AI agent's functioning was developed, detailing the data processing and analysis processes, machine learning methods for identifying hidden patterns, risk forecasting mechanisms, and recommendation generation. The final stage of the methodology involved the use of predictive analytics methods to quantify the potential risk reduction and improvement in occupational safety indicators following the implementation of the AI agent and the DT. The model is verified by comparing the simulated results with empirical data to objectively assess the effectiveness of the proposed approach.

The methodology chosen by the authors ensures the scientific rigour and validity of all stages of the study, from conceptualisation to the assessment of the practical potential of innovative solutions in the field of labour protection. The following materials were used for this study: data from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan; the regulatory framework of the international (in particular, ICAO, ITF regulations, etc.) and national levels (in particular, legislative and regulatory acts of the Republic of Kazakhstan in the field of civil aviation), airline reports, etc.

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

3. Results

The choice of the occupational safety management system in civil aviation of the Republic of Kazakhstan as the object of study is because the passenger and cargo transportation market by air transport in Kazakhstan is the most stable and fastest-growing in the Central Asian region. According to the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan, in January-December 2023, the air transport of the republic transported 13.3 million passengers, which is 20.7% higher than in January-December 2022. Accordingly, the passenger turnover indicator also increased. According to the 2023 results, the amount was 25.9 billion p/km, which was 28.8% higher than the previous year [39].

Volume of services provided to passengers at Airports have also increased by almost a quarter. Their significant growth is observed in Almaty and Astana, where record figures were recorded in 2023: 9 million (+34%) and 7 million (+26%) passengers served. The volume of cargo handled at airports has also increased. At the beginning of the year, this figure has totalled 130,000 tons, which is 16% higher than that in 2022 [40].

However, despite the rapid development in civil aviation, the industry still faces some bottlenecks, particularly in terms of hazardous working conditions. According to the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan, the number of air transport personnel employed in hazardous working conditions during 2008-2024 exhibits complex and ambiguous dynamics (Table 1).

Table 1

Number of air transport workers employed in harmful and hazardous working conditions during 2008-2024, people [41]

Years	Passenger transportation, thousand people	Passenger turnover, million passengers per kilometre	Cargo baggage transported, baggage cargo, thousand million tons	Cargo tuMoreover, million tons per kilometre	Average number of employees			Of these, those employed in harmful and Hazardous working conditions				
					total	including the number of employees		of which are employed on the night shift	employed in conditions that do not meet Sanitary and hygienic requirements (standards)	of which working under the influence		
						which has at least one type of compensation established	of them number of workers			increased noise and vibration levels	increased dustiness and gas contamination of the air in the working area, exceeding the maximum permissible coefficient	unfavourable temperature conditions
2008	2838,8	5549,5	23,7	69,5	4939	2111	1041	--	2115	665	175	245
2009	2758,7	5313,3	21,3	68,0	4912	1767	890	-	1795	333	124	157
2010	3401,18	6517,2	29,2	94,0	5116	751	999	-	1614	772	156	115
2011	4111,48	7859,1	29,4	89,1	5701	2289	2575	-	2052	1899	98	188
2012	4558,72	8795,8	19,6	54,9	5796	2233	3198	98	1809	1744	106	36
2013	4992,97	9704,6	24,0	63,2	6203	2596	3479	1492	710	681	8	10
2014	5447,71	10588,9	19,6	49,2	6733	2633	3570	1633	590	673	8	4
2015	5924,9	11138,6	17,0	42,44	6756	2756	3399	2052	712	723	31	74
2016	6006,12	11073,0	18,1	42,99	7054	2965	3011	3043	1355	871	38	-
2017	7352,17	14384,2	22,4	53,33	7138	3148	3393	3745	1476	989	47	95
2018	7858,53	16176,7	29,1	55,67	7385	3040	3081	3373	2451	1379	59	-
2019	8614,79	16940,3	25,1	54,2	8011	3791	3657	3945	3835	2871	51	70
2020	5489,71	8335,0	24,2	56,2	7480	3461	2909	4646	2144	2080	31	98
2021	9434,05	14815,7	34,0	81,68	7748	3207	2634	4285	2169	2136	34	98
2022	10993,6	20109,3	24,5	54,44	8557	3589	3371	4723	3454	1978	33	93
2023	13347,2	23382,3	24,1	54,37	10346	4737	2265	4397	4086	1762	534	37
2024	14483,3	25438,9	23,8	63,8	11463	4981	2374	4684	4112	1686	276	56

Despite the significant growth of the industries, key performance indicators, such as passenger transportation and passenger turnover, and an increase in the average headcount, there are noticeable changes in the structure and number of employees exposed to harmful production factors. In 2008, 2,111 people were employed in dangerous working conditions. In subsequent years, this figure underwent decreases (for example, to 751 people in 2010) and significantly increased, reaching a peak of 3,791 people in 2019, before the COVID-19 pandemic. Interestingly, after a decline in 2020-2021, the number of such workers increased again by 2022 to 3,589 people.

The dynamics of the number of workers employed in conditions that do not meet sanitary and hygienic requirements are fascinating. If the data for 2008-2011 are missing or not detailed, then since 2012, there has been a significant number of such workers, reaching a maximum of 4,723 people in 2022. This highlights the ongoing significance of issues related to the working environment's adverse effects. An analysis of specific harmful factors revealed that the number of workers exposed to increased noise, vibration, dust, and gas pollution fluctuated but remained significant throughout the study.

Thus, the labour protection indicators of civil aviation personnel in Kazakhstan are characterised by the data provided in Table 2.

Analysis of the presented statistical data on occupational safety indicators for civil aviation personnel in Kazakhstan for 2008-2022 (Table 2) revealed significant trends and fluctuations in in industrial safety dynamics. The study of occupational safety indicators in Kazakhstan's civil aviation sector from 2008 to 2022 reveals a complex and evolving picture. Approximately until 2014, the early period shows a positive trend towards a decrease in the absolute number of injured workers and the injury frequency rate (TIFR). This can be interpreted as the implementation or strengthening of basic measures to ensure occupational safety and increase personnel awareness.

However, subsequent years, especially 2020 and 2021, are characterised by a noticeable increase in casualties and a corresponding increase in TIFR. This surge, which is potentially related to workload dynamics, changes in operations, or even global factors such as the COVID-19 pandemic, highlights the OSH system's vulnerability to external influences and internal reorganisations. Importantly, the fatal injury frequency rate (FIFR) remained relatively low even during these periods, indicating that the most critical risks are still under control.

The most notable year is 2022, which shows significant and dramatic improvements in most key metrics. The sharp reduction in the number of casualties and the TIFR and Lost Time Injury Rate (LTIFR) to the lowest values for the entire study period indicates the effectiveness of targeted measures in improving working conditions and preventing incidents. This result may be attributed to a review of safety protocols, increased training, or the introduction of new technologies. At the same time, the LTISR, which reflects the duration of incapacity, increased in 2022. Further analysis is required to

Table 2

Occupational safety indicators for civil aviation personnel in the Republic of Kazakhstan from 2008 to 2024 [41]

Years	Number of victims, people		Loss of Injury Frequency Rate (TIFR)	Fatal Injury Frequency Rate (FIFR)	Loss of working time, days		Heaviness coefficient traumatis (LTISR)	Total Injury Rate	Lost Time Injury Rate (LTIFR)
	Total (LTI)	including fatalities			Total	including due to accidents			
2008	333	13	67,4225	2,632112	5749	5749	17,2642	3,9053	38,5403
2009	306	19	62,2964	3,868078	4142	4123	13,4738	4,6235	35,6101
2010	266	25	51,9937	4,88663	7150	7150	26,8797	1,9343	33,2645
2011	286	25	50,1666	4,385196	6184	6184	21,6223	2,3201	28,6764
2012	277	18	47,7915	3,10559	6683	6683	24,1263	1,9808	27,3188
2013	275	31	44,3333	4,997582	5110	5110	18,5818	2,3858	25,3420
2014	274	12	40,6951	1,782266	5757	5757	21,0109	1,9368	23,2623
2015	281	21	41,5927	3,108348	5164	5164	18,3772	2,2632	23,7753
2016	287	16	40,6861	2,268217	5618	5618	19,5749	2,0784	23,2571
2017	303	20	42,4489	2,801905	5535	1479	18,2673	2,3242	24,2648
2018	318	22	43,0603	2,979012	5948	5453	17,1478	2,5111	24,614
2019	312	17	38,9465	2,122082	6788	6386	20,4679	1,9028	22,2627
2020	455	17	60,8289	2,272727	4756	4360	9,58241	6,3479	25,5621
2021	472	17	60,9189	2,194115	5853	5731	12,1419	5,0172	18,2635
2022	127	8	14,8417	0,934907	4933	4843	38,1338	0,3891	8,48385
2023	161	17	24,8125	1,632816	9389	5970	34,2321	3,3261	12,3728
2024	175	17	23, 954	1,273580	11200	7278	30,2783	3,1181	12,1126

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

understand analysis is required to understand whether this is due to changes, such as injuries, or to the registration methodological features.

Thus, the data on civil aviation in Kazakhstan indicate a progressive development of the occupational safety system, culminating in significant improvements in 2022. However, the identified periodic instability of indicators highlights the need for continuous monitoring, in-depth analysis of the causes of deviations, and adaptation of safety strategies to maintain sustainable positive dynamics and minimise risks to personnel. This is possible with the synergistic integration of a digital twin of the aviation personnel occupational safety management system and an AI monitoring agent at the aviation enterprises of Kazakhstan, the construction and implementation of which is a multi-stage, high-tech process that requires an integrated approach and integration of various data sources.

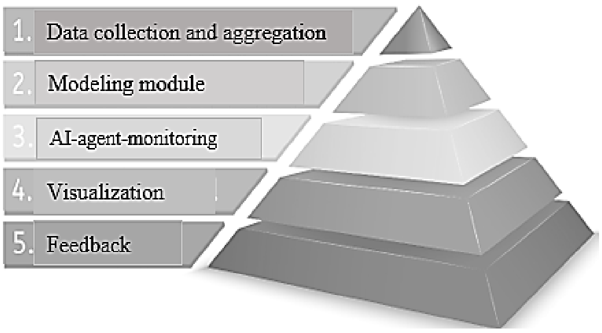

Fig. 2. Architecture and functionality of the synergetic integration of a personnel safety management system's digital twin and an AI monitoring agent at Kazakhstan's aviation enterprises

The initial stage involves collecting and aggregating data from relevant sources, including aircraft specifications, ground equipment, safety systems, repairs, wear, and failures. In parallel, data on the working environment (microclimate, noise, vibration, lighting, and the presence of harmful substances) and detailed personnel information, including qualifications, length of service, work schedules, medical examinations, training, and biometric data to assess fatigue levels, are collected. The integration of statistical data on all types of incidents, including minor injuries, as well as the results of their investigations, alongside current occupational safety regulations, which serve as a reference basis for comparison, is of significant importance. These data create a detailed virtual model covering individual workstations and airfield complexes. Modern CAD systems, BIM modelling, and 3D scanning are used to accurately reproduce physical objects and model processes, considering their dynamics.

Integration with the physical world through an extensive sensor network, including sensors of various parameters, video surveillance systems, wearable devices for monitoring the state of personnel, access control, and equipment telemetry systems, providing a continuous flow of data in real-time, is the key stage that transforms a static model into a dynamic digital twin. To process and visualise this colossal amount of information, a specialised software platform is created that is capable of centralised data storage (Data Lake/Warehouse), processing in real time using streaming technologies, as well as interactive visualisation through 2D/3D models, dashboards and risk maps, while providing modularity for connecting analytical tools, including AI agents.

Implementing such a digital twin will fundamentally transform traditional approaches to occupational safety management, moving them to a qualitatively new level of proactivity and predictability. The system will provide continuous monitoring and real-time diagnostics, enabling operators and labour protection specialists to respond immediately to any deviations from the specified safety parameters. Data aggregated by the digital twin will become a source for predictive analytics and risk forecasting by AI agents.

Using machine learning algorithms, AI agents can identify hidden patterns and correlations and predict the likelihood of accidents, occupational diseases, or technical failures based on multi-factor analysis (e.g., personnel fatigue, equipment wear and tear, and weather conditions). Since the virtual environment of the digital twin serves as an ideal testing ground for the AI agent to simulate various scenarios, including emergencies, without risk to real personnel and equipment, it enables testing new safety protocols, optimising work processes, and assessing ergonomics. In addition, the digital twin, supplemented with an AI agent, will provide personalised risk management and training, offering customised rest programs, additional training or medical examinations based on the analysis of each employee's unique data, as well as allowing realistic simulations to practice actions in dangerous situations.

The digital twin and the AI agent, working in symbiosis, can provide unprecedented transparency and automated control over compliance with occupational safety regulations, simplifying audits, and demonstrating compliance with the highest international safety standards.

Thus, implementing a DT in Kazakhstan's civil aviation occupational safety management system is not only a technological breakthrough but also a strategic investment in the safety of industry personnel.

An algorithm for constructing an AI agent to predict labour safety risks in Kazakhstan's civil aviation was developed to substantiate this hypothesis. Three main machine learning algorithms were selected for their construction: XGBoost, Random Forest, and Logistic Regression.

Each of these algorithms performs a specific function in the overall model:

- XGBoost (extreme Gradient Boosting) is a gradient-boosting algorithm that effectively works with tabular data and accounts for nonlinear relationships between variables. It is used to classify risks, that is, to predict the probability of an incident based on input parameters. Main parameters: input data (X) – NoiseLevel, StressLevel, WorkingHours, AccidentsLastYear, EquipmentAge, FatigueIndex; target variable (y): 1 – if the risk of an incident is high, 0 – if the risk of an incident is low. The algorithm constructs a sequence of decision trees, each of which optimises the errors of the previous one. The initial value is the probability (P(y=1)) compared with the threshold to determine the class (high or low risk). The XGBoost algorithm optimises the loss function by boosting (1):

$$L(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k), \qquad (1)$$

where - loss function (example - log loss), $\Omega(f_k)$ - Model complexity penalty;

- Random Forest is an ensemble algorithm that builds multiple decision trees and combines their results to reduce errors. The main goal of this model is to determine the importance of the factors that most influence the probability of an incident. Main parameters: input data (X) - the same as for XGBoost. The method creates multiple decision trees using random subsets of data and features, evaluating how each variable reduces the model's error. Random Forest uses an ensemble of decision trees (2):

$$f(x) = \frac{1}{T} \sum_{t=1}^{T} h_t(x), \qquad (2)$$

where $h_t(x)$ – forecast of the tree, T – number of trees;

- Logistic Regression is a simple algorithm that uses a logistic function to model the probability of a target variable depending on input parameters. Main parameters: input data (X) - the same as for XGBoost; target variable (y). Logistic Regression calculates the risk probability using a logistic function:

$$P(y = 1|x) = \frac{1}{1+e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)}}, \qquad (3)$$

where β_0 - free term, β_i - weight coefficient for the i variable, and x_i.

The combination of these algorithms enables us to accurately predict risks and gain a deeper understanding of the relationships between parameters. XGBoost is responsible for forecast accuracy, Random Forest helps determine the importance of variables, and Logistic Regression provides transparency in the relationships. As part of the study, a program code was developed to implement machine learning models for assessing labour safety risks at the airport. The software was created in Python using the scikit-learn, XGBoost, Pandas, Matplotlib, and Seaborn libraries. The code provides data loading, pre-processing, model training, evaluation of their effectiveness, and visualisation of the results (Fig. 3).

The training set containing the main factors affecting occupational safety risks was used to test the models: NoiseLevel (noise level), StressLevel (stress level), WorkingHours (working hours per day), AccidentsLastYear (number of incidents over the past year), EquipmentAge (age of equipment in years), FatigueIndex (fatigue index).

The graph (Fig. 4) displays the Receiver Operating Characteristic (ROC) curve for the XGBoost model, illustrating its ability to distinguish between classes (low-risk and high-risk). High risk", and the vertical axis (True Positive Rate) shows the proportion of correctly classified objects as "high risk." The grey dotted line corresponds to the area under the curve (AUC = 0.5) of the random guessing model, while the blue line represents the XGBoost model's performance.

The area under the curve (AUC) is 0.86, indicating the model's high performance. AUC = 0.86 indicates that the model has an 86% probability of correctly ranking a high-risk object higher than a low-risk object. The XGBoost model, with an AUC of 0.86, is well-suited for tasks that require effective identification of risky objects. For example, such a model can identify high-risk workers who require immediate intervention or additional occupational safety measures.

Figure 5 illustrates the significance of input features (factors) as determined by the Random Forest model. The importance values reflect how much each feature affects the accuracy of risk classification. The impact is estimated based on the change in the model error metric after the values of a particular variable are permuted.

The most crucial feature of the model is AccidentsLastYear, with an importance of approximately 0.30 (30%). This suggests that the number of incidents over the past year is a key factor in predicting risk.

Noise Level: The noise level has the second most crucial impact (approximately 0.22). Fatigue Index: The Fatigue Index is the third most important factor (approximately 0.18). High levels of fatigue can lead to decreased attention and physical performance, which increases the risk of amputation.

The stress level also plays a significant role (approximately 0.15). This confirms that workers' psychological state is a crucial factor in risk assessment.

Equipment Age: The equipment age is less critical (approximately 0.08) but still affects the results.

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

```
From google. colab import drive
drive.mount('/content/drive/')
import pandas as pd
, numpy as np
, matplotlib.pyplot as plt
, import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from xgboost import XGBClassifier
from sklearn.metrics import classification_report,
roc_curve, auc, confusion_matrix
data = pd.read_csv('/content/drive/MyDrive/Colab
Notebooks/data/occupational_risk_data_2024.csv')
data = data.drop(columns=['RiskLevel'])
X = data
y = data['RiskLevel']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
xgb_model = XGBClassifier(random_state=42)
xgb_model.fit(X_train_scaled, y_train)
xgb_preds = xgb_model.predict(X_test_scaled)
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
rf_preds = rf_model.predict(X_test)
lr_model = LogisticRegression(random_state=42)
lr_model.fit(X_train_scaled, y_train)
lr_preds = lr_model.predict(X_test_scaled)
xgb_report = classification_report(y_test, xgb_preds, out-
put_dict=True)
rf_report = classification_report(y_test, rf_preds, output_dict=True)
lr_report = classification_report(y_test, lr_preds, output_dict=True)
xgb_fpr, xgb_tpr, _ = roc_curve(y_test, xgb_model.pre-
dict_proba(X_test_scaled)[:,1])
xgb_auc = auc(xgb_fpr, xgb_tpr)
plt.figure()
plt.plot(xgb_fpr, xgb_tpr, label=f'XGBoost (AUC = {xgb_auc:.2f})',
color='blue')
plt.plot([0,1], [0,1], linestyle='--', color='gray')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for XGBoost')
plt.legend(loc='lower right')
plt.show()
plt.figure(figsize=(5,5))
cm = confusion_matrix(y_test, xgb_preds)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Low
Risk','High Risk'], yticklabels=['Low Risk','High Risk'])
plt.title('Confusion Matrix for XGBoost')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
rf_importance = pd.DataFrame({'Feature': X.columns, 'Importance':
rf_model.feature_importances_})
rf_importance = rf_importance.sort_values(by='Importance', ascend-
ing=False)
plt.figure(figsize=(8,6))
sns.barplot(x='Importance', y='Feature', data=rf_importance, pal-
ette='viridis')
plt.title('Feature Importance (Random Forest)')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
xgb_probs = xgb_model.predict_proba(X_test_scaled)[:,1]
sns.kdeplot(xgb_probs[y_test == 0], label="Low Risk", shade=True,
color="blue")
sns.kdeplot(xgb_probs[y_test == 1], label="High Risk", shade=True,
color="red")
plt.title("Predicted Probabilities Density (XGBoost)")
plt.xlabel("Predicted High Risk Probability")
plt.legend()
plt.show()
sns.pairplot(data, hue="RiskLevel", diag_kind="kde", palette="husl")
plt.suptitle("Paired Dependences of Factors and Risk Levels", y=1.02)
plt.show()
print("XGBoost Evaluation")
print(classification_report(y_test, xgb_preds))
print("Random Forest Evaluation")
print(classification_report(y_test, rf_preds))
print("Logistic Regression Evaluation")
print(classification_report(y_test, lr_preds))
```

Fig. 3. Implementation of a digital twin of the airport occupational safety risk assessment software based on machine learning algorithms in Python

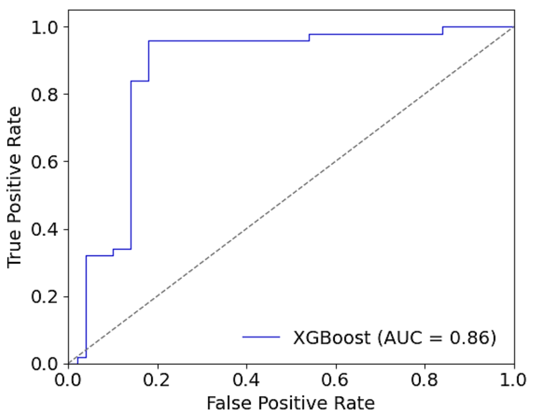

Fig. 4. ROC (Receiver Operating Characteristic) curve for the XGBoost model

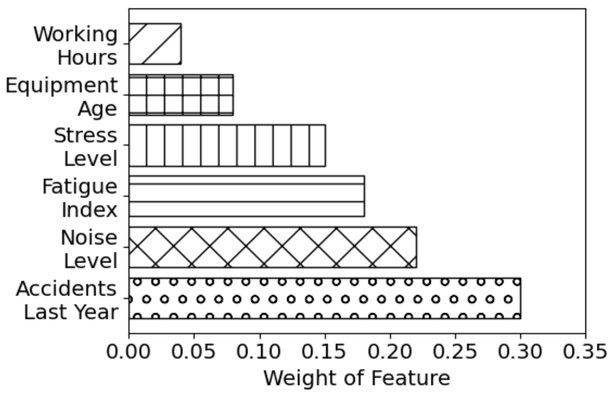

Fig. 5. Importance of the Input Features in the Random Forest Model

Working Hours: Working hours are the least significant factor in this model (less than 0.05).

This suggests that working hours alone are not a primary risk indicator without considering other factors. The factor importance plot demonstrates that the Random Forest model successfully identifies the key variables influencing risks and monitoring incidents to prevent their recurrence.

The graph (Fig. 6) illustrates the even dependencies between the factors (Noise Level, Stress Level, Working Hours, Accidents Last Year, Equipment Age, and Fatigue Index) and the target variable (Risk Level). This is a scatter plot matrix combined with the distribution graph factor.

Fig. 6. Visualisation of the relationship between the following factors (NoiseLevel, StressLevel, WorkingHours, AccidentsLastYear, EquipmentAge, FatigueIndex) and the target variable (RiskLevel)

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ISSN 2663-2012 (online)

The graph allows the assessment of the relationships between the variables and their impact on the risk level.

The distribution shows that high noise levels (NoiseLevel) are more often associated with high risk (RiskLevel = 1). This confirms the significance of this factor in the model. In combination with other factors, such as FatigueIndex or StressLevel, NoiseLevel can intensify risks.

High stress levels are also correlated with high risk. Low-risk workers have significantly lower stress levels than high-risk workers.

The graphs show that working hours (WorkingHours) have a weaker correlation with the risk level. This factor is less significant. The distribution for both risk levels is similar, confirming low dependence.

A strong correlation was found between the number of incidents (AccidentsLastYear) and high risk. Low-risk employees have significantly fewer incidents. When FatigueIndex or NoiseLevel is combined, the number of incidents is the dominant factor. Older equipment (EquipmentAge) is associated with higher risk, but this relationship is less pronounced than other factors. When combined with AccidentsLastYear, this factor can amplify risk but is less influential. High Fatigue Index values are significantly correlated with high risk of cardiovascular disease. Low-risk employees usually have lower fatigue.

The XGBoost, Random Forest, and Logistic Regression models were evaluated based on the following key metrics: precision, recall, F1-score, and overall accuracy. The results show a significant difference in performance between the nonlinear models (XGBoost and Random Forest) and the linear model (Logistic Regression) (Table 3).

Table 3
Performance evaluation of XGBoost, Random Forest and Logistic Regression models

XGBoost Evaluation				
	precision	recall	f1-score	support
0	0.92	0.81	0.86	270
1	0.93	0.97	0.95	730
Random Forest Evaluation				
	precision	recall	f1-score	support
0	0.92	0.81	0.86	270
1	0.93	0.97	0.95	730
Logistic Regression Evaluation				
	precision	recall	f1-score	support
0	0.67	0.59	0.63	270
1	0.86	0.89	0.87	730

The XGBoost model demonstrated high performance with an overall accuracy of 93%. It achieved a precision of 0.92 for the “low-risk” class and 0.93 for the “high-risk” class. The recall of the model was 0.81 for “low risk” and 0.97 for “high risk,” indicating the model’s ability to correctly classify most objects, especially high-risk ones. The F1-score, which balances precision and recall, was 0.86 for “low risk” and 0.95 for “high risk.” These results indicate the strong ability of the model to classify both risky and safe cases.

The Random Forest model showed results similar to those of XGBoost. The overall accuracy was 93%, the precision for both classes was 0.92 and 0.93, and the recall was 0.81 and 0.97 for “low” and “high risk,” respectively. The F1-score values are identical to those of XGBoost, indicating the comparative performance of these two models. Given the similarity of the results, both models can be used depending on the computing resources and training time.

The linear Logistic Regression model performed much worse than XGBoost and Random Forest. The overall accuracy was only 81%, which was 12% lower than that of the nonlinear models. The model accuracy for “low risk” was 0.67, and for “high risk” was 0.86. The recall was 0.59 for “low risk” and 0.89 for “high risk.” This indicates that the model has significant difficulty in identifying low-risk cases. The F1-score confirms this trend: 0.63 for “low risk” versus 0.87 for “high risk.” Thus, Logistic Regression is less effective than the nonlinear models.

The results indicate that XGBoost and Random Forest models are the most suitable for classifying hazardous work risk. They effectively identify both classes and provide high accuracy, recall, and F1-scores. Although delivering a certain level of performance, Logistic Regression is inferior to nonlinear models, especially for tasks with nonlinear dependencies between features.

Building an AI agent involves several interrelated steps, each of which is vital for creating an effective and accurate model. These steps are implemented sequentially, providing a systematic approach to working with data and modelling.

The first stage is data collection and preprocessing. This stage involves collecting data from different sources, cleaning them, eliminating missing values, and normalising or scaling features to ensure the correct operation of the algorithms. This is a fundamental step because data quality has a significant impact on the model’s effectiveness.

The next step is feature selection and engineering, where the most significant variables are identified and new features are created to enhance the model performance.

Subsequently, the data are divided into training and test samples. This is necessary to evaluate the performance of the models: the training sample is used to create the model, and the test sample is used to check its performance on new data.

The main stage is model training. Algorithms such as XGBoost, Random Forest, and Logistic Regression are used. Each model is configured and trained based on the training sample, after which its performance is evaluated using test data.

After training the models, they are evaluated using key metrics such as Precision, Recall, F1-score, and AUC (area under the ROC curve). This allows you to determine which model is best suited for the task.

Next, the importance of features is analysed to determine which factors most significantly influence the forecasts of the model. This makes the models more interpretable, enabling the use of results to inform practical decisions. Based on the obtained data, graphs, tables, and other visualisations are created to understand how the model works and draw conclusions about its practical application.

Moreover, the final stage should involve the creation of an occupational health and safety management system that can independently learn, automatically update, and adapt, thereby increasing future forecast accuracy. Thus, implementing a digital twin of the occupational safety management, combined with an AI monitoring agent, represents the next logical step in the evolution of the occupational safety system in Kazakhstan's civil aviation, opening up new opportunities for creating a safe and efficient working environment.

4. Discussion

The developed methodology for constructing an AI agent for occupational health and safety management systems in civil aviation demonstrates several significant differences between traditional and modern approaches, providing increased efficiency and adaptability in a dynamic and high-risk environment. The proposed architecture's fundamental superiority lies in its ability to deeply integrate semantic data, proactively forecast risks that consider the human factor, and achieve a high degree of automation in the decision-making process.

Unlike simple reflex or model-oriented agents, which are often limited to reacting to predefined patterns or using static models of the world [43], the risk model's methodology focuses on the dynamic construction and continuous adaptation. This is achieved through specialised machine learning algorithms that process multimodal data from the digital twin in real-time (e.g., equipment telemetry, personnel biometrics) and identify hidden, non-linear correlations that form potential threats. This approach enables the AI agent to react to symptoms and predict their occurrence, thereby identifying vulnerabilities in complex interactions among technical systems, human factors, and external conditions.

The developed methodology for building an AI agent for occupational health and safety management systems in Kazakhstan's civil aviation stands out from similar approaches due to its focus on the practical implementation of predictive risk analytics based on robust machine learning models. Unlike conceptual architectures or systems that require highly specialised environments, the proposed approach focuses on creating a functional tool that can be directly integrated into an airline's real operational processes.

The key difference is the modular and scalable software implementation written in Python using proven and widely used libraries, such as scikit-learn, XGBoost, pandas, matplotlib, and seaborn. This ensures that the solution has a high degree of reproducibility, modifiability, and compatibility with existing data centres and IT infrastructures. While many scientific developments of AI agents [44] rely on specific or proprietary frameworks, our proposed methodology emphasises open and flexible tools, simplifying implementation and subsequent support in a real production environment.

Building an AI agent involves successive stages of the machine learning lifecycle, from raw data loading and preprocessing to training, evaluating model performance, and visualising the results. This ensures the transparency and controllability of each stage of agent intelligence formation, which is critical for a field with high-reliability requirements, such as civil aviation. In contrast to deep learning "black boxes" [45], where interpreting decisions can be difficult, this approach utilises models from scikit-learn. XGBoost allows various Explainable AI (XAI) methods to be applied, enabling the understanding of factors influencing risk assessment, which increases user trust and facilitates informed management decisions in labour protection.

In addition, the developed AI agent is not limited to a single forecasting model [46] but utilises an ensemble of different classification algorithms, including XGBoost, Random Forest Classifier, and Logistic Regression. This multi-model approach increases the robustness and reliability of risk forecasts by compensating for the potential shortcomings of individual algorithms and considering different aspects of the data. For example, Logistic Regression can provide more interpretable linear dependencies. Simultaneously, XGBoost and Random Forest can identify complex, nonlinear patterns and feature interactions, which are critical for comprehensive risk assessment in a complex occupational health and safety system. The ability to compare the performance of these models allows the most effective one to be selected for a particular dataset or even to use a combination of them (bagging/boosting) to improve accuracy.

The introduction of analysis elements such as feature importance visualisation (for Random Forest and XGBoost) and the construction of confusion matrices, as well as probability density plots of predicted classes, distinguishes this method from many deep learning "black

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

boxes," particularly [47]. In the highly regulated and responsible field of civil aviation, obtaining a forecast and understanding the factors on which it is based are crucial. Feature importance analysis enables occupational safety system professionals to identify key risk determinants (e.g., specific types of work, environmental conditions, and personnel qualifications), allowing them to develop targeted and justified preventive measures [48]. Confusion matrices, in turn, help estimate specific types of classification errors (false positives and false negatives), which is critical for calibrating the decision threshold based on the error cost.

Thus, the developed methodology, embodied in the presented program code, does not simply offer a theoretical concept of an AI agent but provides a practical, transparent, and scalable tool for predictive analytics of occupational safety risks, which can become a key element in the formation of a proactive safety culture in civil aviation.

5. Conclusions

In the course of the conducted study of the digital transformation of the occupational safety management system in the civil aviation of the Republic of Kazakhstan, a general positive trend towards a decrease in incidents was established, including periods without fatal incidents, which indicates significant achievements in the formation of a safety culture and the effectiveness of the applied preventive measures. Nevertheless, the identified oscillations in statistical series and the episodic growth of some indicators emphasise the need to introduce more advanced, proactive, and adaptive risk management mechanisms to ensure the industry's sustainable development in an increasingly complex operating environment.

In response to the aforementioned challenges, this study developed and scientifically substantiated an original methodology for constructing an AI agent that operates in symbiosis with a digital twin system during intraoperative procedures. The proposed agent architecture, which is embodied in software code that uses high-performance machine learning libraries (such as scikit-learn, XGBoost, and pandas), marks a paradigmatic shift towards predictive occupational safety management. The developed methodology's key distinguishing features are its exceptional practical applicability and a high degree of readiness for operational implementation. This is achieved through a modular software architecture and reliance on widely tested, open-source software, which guarantees unprecedented scalability, configuration flexibility, and seamless integration with existing aviation information and management systems.

Thus, the scientific novelty of the study lies in the substantiation and development of an innovative multimodal approach to the digital transformation of the occupational safety management system in civil aviation, based on the synergistic integration of an AI agent with digital twins for the analysis of complex data and the proactive prevention of occupational risks.

A multimodal approach to predictive risk analytics, based on an ensemble combination of various classification algorithms, ensures enhanced forecast realism and accuracy. This approach enables the effective identification of complex, nonlinear relationships and hidden patterns in digital twins' multimodal data, which are often inaccessible to traditional expert systems or univariate statistical models. Special attention is given in the developed methodology to ensure the interpretability and explainability of the AI agent's decisions. This is achieved through the application of feature importance analysis and detailed representations of error matrices, which is critical for fostering trust among end-users, occupational safety specialists and managerial staff, providing not only highly accurate recommendations but also a deep understanding of their logical justification. This is a fundamental requirement for making informed and effective management decisions in the highly responsible and strictly regulated civil aviation industry.

Thus, the results of this study convincingly support the hypothesis that the strategic symbiosis of digital twins and the developed AI agent possesses transformative potential capable of radically changing the paradigm of occupational safety management. This integrative system enables a transition from traditional reactive incident management to proactive risk modelling, timely identification, and mitigation of potential threats, thereby establishing a fundamentally new, intelligent, preventive, and adaptive safety culture. The outcome of implementing this system will be a significant improvement in operational reliability, optimisation of economic performance, and strengthening of the Republic of Kazakhstan's global aviation competitiveness.

Further scientific research will focus on developing an AI agent for occupational safety management administration in Kazakhstan's civil aviation sector.

Contribution of authors: conceptualisation, methodology – **Kayrat Koshekov, Baurzhan Bakirov**; formulation of tasks, analysis – **Nataliia Levchenko**; development of model, software, verification – **Kayrat Koshekov, Abay Koshekov, Baurzhan Bakirov**; analysis of results **- Natalia Levchenko**, **Kazbek Aldamzharov**; visualisation – **Abay Koshekov, Rustam Togambayev**; writing – original draft preparation – **Kayrat Koshekov**, **Baurzhan Bakirov**; writing – review and editing – **Kayrat Koshekov**, **Abay Koshekov.**

Project information: This project was funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (grant

no. AP19680080 *«Development of a training complex with a system of engineering support for the technical operation of military and special aviation transport equipment»*.

The overwhelming majority of training programs for aviation devices, systems, and units currently used in the Republic of Kazakhstan are outdated. Ordering training stands that meet modern requirements is as expensive as a real aircraft unit, instrument, or system. Using three-dimensional models and virtual reality technologies will enable the creation of virtual training benches that meet modern requirements for training aviation technical personnel, replicating them with minimal costs, solely using virtual reality equipment.

According to the conducted analyses, the most appropriate software life cycle model was chosen. It was an iterative incremental model of creating a training application for full-time, part-time, and distance education students on the aviation module "Aerodynamics, Design, and Systems." This model is considered the fundamental basis of modern software development approaches. A certain duality characterises the model:

- this model is considered iterative from the perspective of the application life cycle because it implies repeated repetition of the same stages;

- from the point of view of application development (adding proper functionality to it), the model is considered incremental.

The relevance and importance of the proposed scientific solutions provides a significant economic effect because it is 100% safe for students, replaces training in practice, no airport pass is required, no risk of possible damage to the aircraft or injuries during training, organisation of practices with an unlimited number and without significant costs, taking into account expensive resources and time, the possibility of stopping the simulation to discuss the problem with the trainee, simulation of any weather conditions and surface conditions, simulation of risky situations. In the context of online learning implementation, organising virtual internships, practical, and laboratory classes to ensure the practical competencies of future specialists becomes a significant project.

Due to the importance of the project for the aviation of Kazakhstan, the project aimed to develop, test, and implement the technology of designing digital simulators with engineering support system for the technical operation of military and special aviation transport equipment based on 3D-modelling and virtual reality to ensure high-quality theoretical and practical training following the requirements of international standards and recommended practices of ICAO, EASA, and IATA.

Several scientific and practical tasks were solved to achieve the set goal. First, design technologies were developed based on methods and algorithms for transforming design documentation into the likeness of real objects. Databases of 3D models of photorealistic quality instrument panels and control elements for military and special aviation transport equipment, along with their textures, have been created. Structuring and storing files according to the criteria of optimising the speed of access to information for further design of digital simulators. This project was executed by **Kayrat KOSHEKOV, Abay KOSHEKOV** and **Baurzhan BAKIROV**.

Second, a hardware-software complex of digital simulators for the maintenance and operation of military and special aviation transport equipment was designed: an anti-blanketing machine, slurry machine, ambulatory lift, autotrap, container transloader, belt transloader, baggage tractor, driver tractor, driverless tractor, and armoured vehicles. The project's executors are **Rustam TOGAMBAYEV, Abay KOSHEKOV and Baurzhan BAKIROV.**

Third, a simulator complex with an engineering support system was developed for the technical operation of military and special aircraft transport equipment. Created client-server logic for the application, allowing the control of several connected clients from one server. **Rustam TOGAMBAYEV, Kazbek ALDAMZHAROV** and **Nataliia LEVCHENKO** are the executors in this area.

Fourth, a Commercialisation Centre was established by organising training and issuing certificates and a licence to operate special equipment at the aerodrome, according to the requirements of international standards and recommended practices of ICAO, EASA and IATA. **Kayrat KOSHEKOV, Nataliia LEVCHENKO** and **Abay KOSHEKOV** were involved in developing technical documentation and organisational issues related to the opening of the Centre.

Fifth, developing an intelligent system to assess trainees' practical competencies is an essential project element. The results of research in this direction are presented in this article. The executors are **Rustam TOGAMBAYEV, Kayrat KOSHEKOV, Nataliia LEVCHENKO** and **Abay KOSHEKOV.**

Approbation of the results of experimental research on the project in the conditions of JSC 'Almaty International Airport" allows us to assert that the following problematic issues of the organisation of educational and production processes are successfully solved: high level of correspondence of real objects and processes in virtual training, simultaneous multi-user scenarios for coordinated training of the team, individual responsibility for the actions performed in the training process, reducing the influence of the human factor on the training process. A standard for training personnel in the air transport industry and an innovative approach based on interactive training methods are being developed.

ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

Based on advanced information and communication technologies, the authors of the project have developed and implemented at JSC ‘Aircraft Repair Plant No. 405’ a management system, which allows, thanks to the developed simulators, not only to create interactive scenarios based on virtual reality technologies to ensure deep immersion in the studied material but also to conduct the educational process with complete administration and data analysis. The software is implemented on the Moodle platform, which provides a high level of security and flexibility to customise the process of publishing training and studying materials based on the time spent learning the material to fix correct and incorrect actions. Also advantageous is the ability to integrate popular services: Zoom, Google Meet, Big Blue Button, and Google Calendar. **Baurzhan BAKIROV** and **Kazbek ALDAMZHAROV** developed the structure and model of the management system and educational platform software.

In addition, due to the project implementation, a new concept of methodological support for the maintenance and operation of military and special aviation transport equipment was proposed, with modelling of standard and abnormal situations during operation for practical training. Each type of equipment includes four types of content: lectures with textual content, video materials, test control tasks, and simulator-based practical exercises. Approbation of the methodological support and software of the educational process management system in the conditions of JSC “Aircraft Repair Plant No. 405” showed many advantages for application: high speed of loading of educational material when using the web version is much higher, guaranteed correct display of content, fast and unlimited creation of copies of materials in the conditions of complex production process. **Rustam TOGAMBAYEV, Baurzhan BAKIROV, Nataliia LEVCHENKO** and **Kazbek ALDAMZHAROV** were engaged in experimental research and development of the concept and implementation of methodological support.

The project is significant at the international level in the modernisation of education and development of information and telecommunication technologies, aircraft engineering, intellectual technologies, digital signal and image processing.

This project’s implementation contributes to the development of innovative directions in aviation science, such as the application of artificial intelligence in knowledge assessment and the use of technical vision, machine learning, Deep Learning, Data Science and Big Data.

Conflict of Interest

The authors declare that they have no conflict of interest related to this research, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

This research has been funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No.AP19680080). «Development of a training complex with a system of engineering support for the technical operation of military and special aviation transport equipment».

Data Availability

The code for launching the developed diagnostic monitoring system is available at the link https://colab.research.google.com/drive/1NFBPytQjGwpB8abd8nlCzcy9NDkPxEsy?usp=sharing

Use of Artificial Intelligence

The authors confirm they did not use artificial intelligence methods while creating the presented work.

All the authors have read and agreed to the published version of this manuscript.

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Received 14.06.2025, Received in revised form 15.09.2025
Accepted date 03.11.2026, Published date 08.12.2025

ЦИФРОВА ТРАНСФОРМАЦІЯ СИСТЕМИ УПРАВЛІННЯ ОХОРОНОЮ ПРАЦІ В ЦИВІЛЬНІЙ АВІАЦІЇ ШЛЯХОМ СИНЕРГЕТИЧНОЇ ІНТЕГРАЦІЇ ТЕХНОЛОГІЙ ЦИФРОВИХ ДВОЙНИКІВ ТА ШІ-АГЕНТІВ

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Предметом дослідження є цифрова трансформація системи управління охороною праці в цивільній авіації. Стрімке нарощування обсягів вантажо- та пасажиропотоку в Республіці Казахстан, зумовлене унікальним геополітичним положенням країни в центрі Євразії, пов'язане зі зростаючими ризиками для працівників, що робить перегляд існуючих систем управління охороною праці критично необхідним. Традиційні підходи щодо управління охороною праці, часто орієнтовані на реактивне усунення наслідків, демонструють свою недостатню ефективність в умовах динамічного розвитку високотехнологічної галузі, де кожен інцидент тягне за собою серйозні економічні, репутаційні та соціальні наслідки. Підвищити рівень виробничої безпеки можливо за умови застосування передових цифрових технологій, зокрема, технологій цифрових двійників і ШІ-агентів, здатних завдяки самонавчанню, безперервно акумулювати, обробляти і передавати величезні масиви даних в реальному часі, створюючи комплексну картину функціонування всієї системи управління охороною праці авіапідприємства. **Метою дослідження** є обґрунтування доцільності модифікації системи управління охороною праці в цивільній авіації Республіки Казахстан завдяки синергетичної інтеграції технологій цифрових двійників та ШІ-агентів у ключові функціональні процеси. **Результати.** Ключовим внеском даного дослідження є запропонований алгоритм розробленого ШІ-агента, спроектованого спеціально для інтеграції в систему управління охороною праці авіапідприємств Казахстану. Детально описується його архітектура, принципи функціонування та алгоритми взаємодії з великими даними, що надходять від цифрових двійників різних елементів авіаційної системи: від стану повітряних суден і наземного обладнання до психофізіологічних показників персоналу та особливостей робочого середовища. Цей алгоритм дозволяє ШІ-агенту не тільки виявляти аномалії, але й будувати предиктивні моделі, завчасно сигналізуючи про потенційні загрози. Візуалізовано результати проведеного ШІ-агентом розрахунку ризиків у системі охорони праці працівників цивільної авіації, що демонструють його високу ефективність у виявленні вразливостей, прогнозуванні критичних ситуацій і формуванні обґрунтованих, персоналізованих рекомендацій щодо їх запобігання. Результати досліджень свідчать, як проактивний моніторинг і аналіз, що виконується ШІ-агентом на основі даних цифрового двійника, може істотно знизити ймовірність ситуацій, пов'язаних з травматизмом та професійними захворюваннями. **Висновки.** Запропонований підхід до модифікації системи управління охороною праці на підприємствах цивільної авіації базується на синергетичній інтеграції цифрових двійників і ШІ-агентів, при якому управління ризиками переходить від реактивного усунення до попереджувального моделювання та нівелювання потенційних загроз. Створення системи управління охороною праці на авіапідприємствах країни, заснованої на застосуванні ЦД і ШІ-агента, суттєво підвищить конкурентоспроможність цивільної авіації Республіки Казахстан на світовому ринку, позиціонуючи її як лідера в застосуванні високотехнологічних рішень для забезпечення безпеки праці та сталого розвитку.

Ключові слова: цивільна авіація; шкідливі умови праці; безпека праці; система управління охороною праці; травматизм; професійні захворювання; цифровий двійник; ШІ-агент; цифрова трансформація.

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ISSN 1814-4225 (print)
ISSN 2663-2012 (online)

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