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IMPROVING THE ECONOMIC EFFICIENCY OF DATA MANAGEMENT AND ARTIFICIAL INTELLIGENCE IN DIVERSE AIRLINE MARKET CONDITIONS

Abdul-Khassen Nurlanuly
Doctoral Student PhD
Department of Economics and Entrepreneurship
L. N. Gumilyov Eurasian National University
Satpayev str., 2, Astana, Republic of Kazakhstan, 010000
ORCID: https://orcid.org/0009-0001-6450-0747

Serik Serikbayev
Candidate of Economic Sciences, Senior Lecturer
School of Law and Public Administration
NARXOZ University
Zhandosova str., 55, Almaty, Republic of Kazakhstan, 050035
ORCID: https://orcid.org/0000-0002-5479-2109

Aizhamal Aidaraliyeva
Candidate of Economic Sciences, Associate Professor
ORCID: https://orcid.org/0000-0002-7291-2426

Nazym Akhmetzhanova
PhD Doctor, Senior Lecturer*
ORCID: https://orcid.org/0000-0003-1533-1606

Inna Stecenko
Doctor of Economic Sciences, Professor
Faculty of Transport and Management
Transport and Telecommunication Institute
Lauvas str., 2, Riga, Latvia, LV-1019
ORCID: https://orcid.org/0000-0002-0277-286X

Almira Saktayeva
Candidate of Economic Sciences, Associate Professor
Department of Economics, Management and Finance
Sarsen Amanzholov East Kazakhstan University
30th Gvardeiskoi Divisii str., 34, Ust-Kamenogorsk, Republic of Kazakhstan, 070002
ORCID: https://orcid.org/0000-0002-9538-4494

Oxana Kirichok
Corresponding author
PhD Doctor, Associate Professor
Department of Economics and Administration
Caspian University
Dostyk 85A ave., Almaty, Republic of Kazakhstan, 050000
E-mail: oxanakirichok1@gmail.com
ORCID: https://orcid.org/0000-0003-1059-4917

*Institute of Digital Economy and Sustainable Development
Zhangir Khan University
Zhangir Khan str., 51, Uralsk, Republic of Kazakhstan, 090009

The object of the study is a complex of management practices and organizational mechanisms, which ensure implementation of data analysis and artificial intelligence technologies into airline operations. The study deals with the problem of quantitative evaluation of the impact from the extent and quality of data & artificial intelligence solutions on the key indexes of airline managerial efficiency.

The following results have been obtained:

– analysis of the digital maturity level with financial and operational key performance indicators of airlines has identified a considerable intercluster differentiation;

– a one-point increase in artificial intelligence digital maturity is associated with the growth of operating margin by 1.98%, whereas the 1% increase of data investment share contributes to its growth by 1.12%;

– two standard models of data & artificial intelligence innovation project management, which demonstrated various outputs in studied institutional contexts.

The produced findings can be explained by the fact that translation of technology investments into financial outcomes is mediated by the quality of management system, which includes strategic alignment, coordinating organizational changes and a system of investment efficiency evaluation.

The specifics of obtained results possess a dual nature: on the one hand, they confirm the universally positive effect from data & artificial intelligence implementation; on the other hand, they highlight the critical significance of context-dependent, cluster-specific management strategy.

The practical significance of this study lies in the formation of evidence base for making justified decisions by airline management, as well as producing defined tools for maximizing the output from investment in digital technology

Keywords: data, artificial intelligence in aviation, digital transformation, operational efficiency, panel regression, cluster analysis

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1. Introduction

The contemporary stage of global economy development is characterized by accelerating digital transformation, which drastically alters conventional business models and competitive landscape. In the field of aviation, which represents a high-tech capital-intensive segment of transportation system, this process is accumulating greater significance.

The increasing volatility of demand, cost price growth, tightening of ecological regulations and growing customer expectations in terms of personalized service form a complex of challenges, which cannot be adequately addressed solely via the conventional management approaches. In these conditions, a strategic implementation of big data and AI-based systems seizes to be a mere technological trend, becoming a mandatory factor of stable improvement. Data & AI offer profound opportunities for optimization of key processes: from predictive technical aircraft maintenance and dynamic profit management to hyper-personalization of marketing communications and Customer Experience.

However, despite the evident potential and growing body of investment, digital transformation in airlines demonstrates a significant variability. Technology investments, which are comparable in scale, can lead to fundamentally different business outcomes, quality of management practices and organizational mechanisms, ensuring implementation and integration of innovations.

Therefore, relevance of the research question is justified by contradiction between technological capabilities and managerial efficiency of their implementation in practice in the field of aviation.

2. Literature review and problem statement

In recent years, the issue of digital transformation has occupied one of the central places in discussions about the sustainable development of the transport industry. The rapid improvement of data processing technologies and artificial intelligence opens up new horizons for airlines to improve operational efficiency and optimize financial performance. In parallel with this process, an extensive body of the study is being formed in the academic environment on various aspects of the implementation of digital solutions in the aviation business.

The analysis shown in the study [1] is aimed at investigating the impact of digital transformation on operational stability of airlines; the authors apply, in particular, regression models for evaluation of outputs from technology investments. Despite the methodological validity of such approach, the main focus of this study is placed on macroeconomic determinants, whereas the internal organizational mechanisms, mediating the transformation of technology investments into defined financial indexes, remain unrevised. This omission declines the practical value of conclusions of this study for managers, who are responsible for digital initiatives implementation on a corporate level.

The study [2] represents a valuable contribution in understanding the connection between data management and customer experience in transportation industry, offering a detailed classification of digital tools. The drawback of this study lies in its solely qualitative and descriptive nature as a lack of quantitative verification of proposed hypotheses does not enable to establish statistically significant causality and assess the extent of the impact from the factors in question.

The study [3] is dedicated to the establishment of a system of indexes for monitoring the financial state of airlines. However, the proposed array of indexes inflicts a significant limitation: it does not include the criteria, which allow to assess the digitalization level, implementation of data analysis-based decisions or the extent of artificial intelligence technology use. Apart from this, the system structure itself has a static nature and does not take into account accelerating dynamics of technological changes in the area, as well as fundamental differences in business models and institutional environment of companies from various regions. As a result, the established model turns out to be improper in terms of comparative analysis of the impact from data & AI investments on the operational and financial airline activity.

The publication [4] thoroughly analyzes traditional strategies of cost price management (CASK) in aviation, establishing a clear link between operational indexes and financial stability. However, the focus of the study is limited by the conventional cost reduction tools. Thus, the study does not address the question of how new data analysis-based tools transform the very nature of cost management and create the sources of higher-level effectiveness.

The study [5] is devoted to the evaluation of economic mechanisms of artificial intelligence integration for operational cost reduction optimization. The authors highlight the potential of data analysis technology for cost reduction via improvement of fuel efficiency and predictive maintenance. Nevertheless, the suggested approach is limited by theoretical analysis and is not supported by empirical assessment based on data from real companies. There has not been developed a clear method for quantitative calculation of return on investment (ROI) from digital projects, which does not enable applying the study conclusions to justified management decisions and investment budget formation.

The publication [6] is focused on the assessment of economic effect from machine learning systems implementation for predictive maintenance. There are calculations of potential cost reduction in repairs and increase in flying time of an aircraft. Yet the analysis is based on model data and ideal scenarios, which do not take into account real organizational implementation barriers such as a necessity to adapt working processes, educate the personnel and integrate with legacy system. As a result, the produced cost reduction evaluation is hypothetical and can deviate from the factual outcomes, achieved by a specific company in the real-world conditions.

The study [7] analyzes transformations of airline business models under the influence of digital platforms, drawing the attention to the change in value chains. However, the limitation of this study is its theoretical, conceptual nature, which is not supported by the comparative analysis of real company cases from the various market clusters, thus not allowing to assess the success rate of such transformations in practice.

The paper [8] systematizes various applied solutions on the basis of artificial intelligence in air logistics and evaluates their overall economic impact on operational efficiency. The main disadvantage of this study is its generalizing, descriptive nature: there is an absence of economic efficiency analysis of various solutions depending on the company scale or its business model. The lack of framework for investment prioritization in terms of logistic AI-solutions decreases the practical appeal of this study for managers, who need to choose among many technological options.

The paper [9] attempt to conduct quantitative analysis of AI influence on the reliability of a vehicle fleet and cost reduction, using regression analysis methods. Despite the progressive methodology, the sample of this study appears to be narrow and unrepresentative for the entire segment; moreover, there is a lack of consideration of strategic maturity of companies in terms of data, which undermines the possibility to extrapolate the produced results.

The study [10] is focused on economic aspects of optimization algorithms implementation for airline scheduling and resource management. The author points out that the main merit of such systems is based not on the algorithmic complexity itself but on their ability to generate measurable financial gain. The study lacks the long-term effect analysis. The proposed effectiveness evaluation model considers short-term optimization but does not take into account how changes produced by the system influence the strategic indexes such as network stability, passenger loyalty and the adaptability of a company to crises, which possesses the decisive power for full investment evaluation.

The paper [11] systematizes modern achievements in the segment of AI application for airline profit management. Although the review is quite extensive, it suffers from a lack of critical analysis: the authors do not outline the conditions, in which some approaches are more effective than others.

The publication [12] delves into the set of distribution problems and profit management in digital environment, highlighting the increasing complexity of corresponding systems. However, its conclusions possess rather indicative nature, predicting further complication but not suggesting viable managerial goals or adaptation strategies for companies with various levels of digital maturity.

The study [13] is dedicated to building AI-driven financial models for airlines, proposing appealing methodological approaches to forecasting. The disadvantage of this study is its hypothetical nature since the proposed models are not validated by existing long-term time series data in market volatility conditions, which leaves the issue of their practical reliability unaddressed.

The paper [14] explores the influence of big data on the innovations in airline business models, highlighting the potential of new value generation. A critical aspect left unattended – the rate of transformation – might not consider the depth of structural and technological limitations.

The study [15] analyzes the relationship between digitalization, productivity and competitiveness within developing markets, bridging an important regional gap. Nevertheless, the focus mostly lies on macro-level, whereas the meso-level of corporate management practices, which directly impact the success of digital initiatives, is not fully explored.

The publication [16] offers economic analysis of digital platforms in aviation, drawing the attention to network effects and market concentration. Despite its theoretical profoundness, the article contains a limited number of empirical examples, and its conclusions are poorly adapted to producing specific recommendations for acting managers, who are responsible for digital transformation in their respective companies.

The paper [17] raises an important aspect of managerial economics – the assessment of investments in cybersecurity of aviation systems as a part of general strategy of risk and cost management. The authors accentuate the link between technological reliability and financial losses from idleness or data breaches. Nonetheless, the study lacks the economic-mathematical model, which would allow to calculate the optimal level of investment in cybersecurity, balancing the immediate costs and potential losses. This leaves the issue of quantitative budget justification in terms of data and system protection, which is essential for management, unaddressed.

The literature review, which was conducted, has identified a substantial gap in existing academic research. On the one hand, a significant number of studies is devoted either to the macroeconomic analysis of the field or technical description of distinct artificial intelligence and data analysis technologies. On the other hand, there are qualitative studies of business-models and managerial cases, yet often they lack quantitative assessment and comparative cross-regional dimension. A critical area on the cusp of these approaches remains explored insufficiently – the meso-level of corporate management, where technological opportunities transform into specific financial outcomes through the lens of managerial practices, organizational mechanisms and strategic alignment.

Hence, existing study does not provide a comprehensive answer to the key practical question: how and to what extent the quality of corporate management mediates the transformation of data & AI investments into concrete financial outcomes for airlines, operating in diverse market conditions.

On the one hand, there is a shortage of publications, which could quantitatively assess the strength of this connection beyond the theoretical models or single case study descriptions. On the other hand, the studies, which attempt the quantitative assessment, often overlook fundamental industry heterogeneity: core differences between business models, level of market development and institutional environment, which could drastically change the effect from the same technology investments. Thus, there is a gap in the study of the problem of economic efficiency of airline data management and artificial intelligence in diverse markets.

It is necessary to empirically assess the impact of technological maturity level in data & AI on key indexes of airline effectiveness, while controlling the role of managerial mechanisms and stratifying the analysis by strategic clusters of companies.

3. The aim and objectives of the study

The aim of the following study is the economic efficiency of data and artificial intelligence management in airlines in diverse market conditions, this will form the evidence base for sound strategic planning of digital investments in the aviation industry.

To achieve this aim, the following objectives were accomplished:

– to conduct a comparative analysis of the digital maturity level with financial and operational KPIs of airlines from selected countries, grouped into strategic clusters;

– to determine the presence or absence of the link between the level of data & AI system implementation and the key indexes of managerial effectiveness in airlines by applying the methods of correlation and panel regression analysis;

– to form standard management models of innovative Data & AI projects in airlines on the basis of case analysis and to assess their efficiency in various institutional contexts.

4. Materials and methods

The object of the study is a complex of management practices and organizational mechanisms, which ensure implementation of innovations based on data analysis and artificial intelligence technologies into airline operations.

The study hypothesis underlies in the assumption about the correlation between digitalization level and economic efficiency of artificial intelligence and data management in diverse airline market conditions. Prior to the study, it was assumed that this correlation is positive and significant.

Prior to the empirical analysis several initial assumptions were made:

– publicly available financial and non-financial reports of European Union (EU) airlines substantially represent the real scale and directions of data & AI investments;

– the expert reconstruction of digital maturity indexes and data investment shares, which is based on the collection of open sources, industry benchmarks and analytical reports, ensures the appropriate validity level for the inter-firm comparison;

– the selected strategic clusters are internally consistent according to the key features of a business model, while the fixed effects in panel regression analysis models allow to properly isolate the impact of the time-invariant institutional and organizational characteristics of the companies.

Additionally, in the course of the study the following simplifications were made:

– the complex notion of digital maturity was aggregated in the limited number of integral indexes (AI_MATURITY, DIG_CX_SCORE), which inevitably negates the separate technological and organizational nuances of specific decisions;

– dynamic and non-linear effects of data & AI implementation, including time lags between the investments and financial outputs, were considered in an averaged form within the annual panel observations;

– the model does not account for the shocks of exogenic nature (regulatory changes, geopolitical events, fuel market fluctuations), and their impact was approximated throughout the fixed effects and the general time structure of the data.

This study uses the following methods: strategic cluster analysis, content-analysis for creating composite indexes, comparative statistical analysis, Spearman's rank correlation analysis, panel regression analysis with fixed effects, case-study method.

The airlines from the European Union countries have been selected since this regional union is an indicative example of diverse market due to its newly acceded members.

The representative sample displaying the market structure of air transportation in EU has been created according to the "National Leader" principle. The final data set included the largest in terms of passenger traffic airlines, which had a state registration in each of the EU countries, which ensured a full state coverage and consideration of regional specifics. To conduct content analysis, which took into account fundamental differences in business models, the entire data set was subdivided into two strategic clusters (A and B):

1. A-cluster: Full-Service Network Carriers (FSNC). The criterion for being attributed to this cluster was orientation towards providing comprehensive service, including multilevel product, the route network "habo-spock", being in global alliances and the focus on attracting corporate segment. There are the following national leaders in this cluster: Lufthansa (Germany), Air France (France), KLM (The Netherlands), ITA Airways (Italy), LOT Polish Airlines (Poland), TAP Air Portugal (Portugal), Finnair (Finland), Austrian Airlines (Austria), Aegean Airlines (Greece), Brussels Airlines (Belgium), Croatia Airlines (Croatia), TAROM (Romania), Cyprus Airways (Cyprus), Luxair (Luxemburg), Air Malta (Malta), SAS Scandinavia Airlines (Denmark/Sweden), Nordica (Estonia), Air Slovenia (Slovenia).

2. B-cluster: Low-Cost Carriers, LLC. The criterion for being attributed to this cluster was business model, focused on minimization of cost price via simplified service, point-to-point routes, high park utilization and prevalence of direct digital sales. This cluster includes: Ryanair (Ireland), Wizz Air (Hungary), AirBaltic (Latvia), Eurowings (Germany, an LLC-model-based subsidiary of Lufthansa Group), Transavia (The Netherlands and France, a subsidiary of Air France-KLM Group). Moreover, this category includes airlines, which business model combines the elements of a low-cost model and regional or charter specialization: Smartwings (Czech Republic), Bulgaria Air (Bulgaria), Avion Express (Lithuania), Air Explore (Slovakia).

This structuring of the sample allows not only to ensure its representativeness but also to provide the basis for hypothesis testing regarding contextual dependence of the effects from data & AI technology implementation. Differentiation according to the business model provides an opportunity to analyze how the strategic choice of a company – orientation towards service-based differentiation (FSNC) or towards the cost leadership (LLC) – modulates the translation of technology investments into operational and financial results. Inclusion of transnational groups along with national champions in each of the clusters allows to consider the impact of scale and avoid systematic bias in conclusions.

The following indexes were used for assessment:

– AI_MATURITY – AI maturity index (1–5), calculated based on the expert analysis of public reports, press releases and industry publications;

– DATA_INV – Data Science & AI investment share in operating expenses, % (assessment based on S&P Global and benchmark reports);

– DIG_CX_SCORE – index of customer experience digitalization (0–100), calculated according to the method of weighed evaluation of personalization, application functionality and loyalty programs.

Financial and Operational KPIs (factual):

– OP_MARGIN – operating profit margin, % (source: annual financial reports of airlines);

– ASK_COST – cost per available seat kilometer (CASK), cents (source: ICAO Data+, Eurostat reports);

– FUEL_EFF – increase in fuel efficiency by 2021, % (source: reports on sustainable airline development, EUROCONTROL);

– CUST_NPS – customer loyalty index (Net Promoter Score), scores (source: Skytrax, open ratings).

Company grading was performed using digital maturity level-based classification. Digital maturity was represented by integral characteristic of organization (or its distinct processes), displaying the extent and effectiveness of using digital technologies, data and competencies for achieving strategic goals, transforming business models and creating stable competitive advantages. The digital maturity levels:

– Level 1. An airline with an entirely outdated IT-infrastructure: manual booking via a call center or ticket offices, a lack of digital document flow, carriage planning and scheduling is performed manually on a paper medium or in simple tables. There is an absence of data analysis systems, a smartphone application, digital channels of communication with the customers;

– Level 2. The early stage of digitalization: a basic system of booking is implemented (for example, a legacy system of Global Distribution System integration), there are simple tools for reporting automation but the processes remain disjointed. There could exist a static website for booking but there is no personalization, the smartphone application has a limited functionality (for example, only online check-in). The data is collected but not utilized for analytics or forecasting;

– Level 3. A modern Customer Relationship Management and a unified data platform, which allows to generate segmented offers, are implemented. There is a smartphone application for customers and employees, the main processes are automated (check-in, baggage);

– Level 4. Utilization of predictive analytics for dynamic pricing and demand forecasting. Digital twins of engines for predictive maintenance. AI-chatbots deal with the >80% of customer enquiries;

– Level 5. An airline functions as a platform. There is a travel ecosystem (hotels, taxi, insurance) with a uniform interface. Generative AI is used for a fully personalized trip planning and autonomous resource management.

For econometric model quality assessment, the following were used:

– R^2 coefficient of determination (within for panel models);

– F-statistic and p-value for overall evaluation of model significance;

– the Durbin-Watson statistic for autocorrelation in the residuals;

– the Hausman test to choose between fixed effects and random effects.

Data processing was performed using Python (pandas, numpy, statsmodels, linearmodels and scipy libraries) on Jupyter Notebook platform (USA).

Informational and empirical database was derived from: annual corporate reports and sustainable airline development reports; press-release databases (PR Newswire); industry analytical reports (IATA, S&P Global, McKinsey); Eurostat, ICAO statistical databases.

5. The assessment of the relationship between the efficiency of data management and artificial intelligence in diverse airline market conditions

5. 1. The comparative analysis of the digital maturity level and financial and operating key performance indicators of the airlines and their clustering

For empirical testing of the hypothesis regarding the link between digitalization level and economic efficiency a comparative analysis of key indexes by strategic airline clusters was conducted. This allows to clearly compare the initial data: the level of technology investments (AI_MATURITY, DATA_INV), the extent of digitalization of customer experience (DIG_CX_SCORE) and resulting financial and operating metrics (OP_MARGIN, ASK_COST, FUEL_EFF, CUST_NPS). The summary results by the end of the study period are presented in Table 1.

The consolidated view represented in Table 1 clearly illustrates a stable positive connection between the level of technological development and key indexes of efficiency. It can be observed empirically that the companies with increased indexes AI_MATURITY and DATA_INV, as a rule, achieve more impressive operational and financial results. Concrete evidence of this statement can be seen in the example of Ryanair, which, having the indexes 4.5 and 5.5% respectively, demonstrates the record operating margin of 12.7% and minimum cost price of 5.2 cents per ASK. This case evidently displays that consecutive technology investments, implemented into the core of a business model, are able to generate measurable competitive advantage.

Table 1

Comparative analysis of data & AI digital maturity and key indexes of airline efficiency (2021–2025, mean value)

Airline	AI_MATURITY (1–5)	DATA_INV (%)	DIG_CX_SCORE (0–100)	OP_MARGIN (%)	ASK_COST (c.)	FUEL_EFF (Δ%)	CUST_NPS (units)
A-cluster. Full-service network carriers (FSNC)							
Lufthansa	4.2	5.1	78	4.8	8.9	+3.5	68
Air France	4.0	4.9	80	6.3	8.5	+4.1	70
SAS	3.0	3.5	70	–2.1	10.1	+1.9	60
TAP Air Portugal	2.8	3.0	65	1.5	9.8	+2.0	58
Austrian Airlines	3.3	3.8	72	2.5	9.5	+2.5	62
Brussels Airlines	2.9	3.2	68	0.8	10.3	+1.8	59
Aegean Airlines	3.6	4.0	77	5.5	8.7	+3.8	71
ITA Airways	3.1	3.6	69	–1.5	10.5	+1.7	57
Cyprus Airways	2.5	2.7	60	0.2	11.0	+1.0	52
Luxair	2.7	2.9	63	1.8	9.9	+2.2	56
Air Malta	2.4	2.5	58	–0.5	11.2	+0.9	50
LOT Polish Airlines	3.4	3.9	74	3.8	9.0	+3.0	66
Finnair	3.7	4.2	76	4.2	8.8	+3.3	69
Croatia Airlines	2.6	2.8	62	0.5	10.6	+1.5	54
TAROM	2.3	2.4	56	–2.5	11.8	+0.7	48
Air Slovenia	2.2	2.3	55	–1.0	11.5	+0.8	49
Nordica	2.1	2.2	53	–1.8	12.0	+0.5	47
B-cluster. Low-cost carriers (LCC)							
Ryanair	4.5	5.5	85	12.7	5.2	+6.0	75
Wizz Air	3.2	3.8	76	5.8	6.1	+5.2	69
AirBaltic	3.8	4.5	81	8.1	6.3	+5.5	73
Eurowings	3.0	3.6	73	4.2	7.2	+3.9	65
Transavia	3.1	3.7	74	5.0	6.9	+4.0	67
Smartwings	2.9	3.3	70	3.0	7.8	+3.2	61
Bulgaria Air	2.7	3.0	67	2.2	8.1	+2.8	58
Avion Express	2.8	3.1	68	3.5	7.5	+3.5	60
Air Explore	2.5	2.8	65	2.8	8.3	+2.5	57

However, the analysis identifies trajectory heterogeneity even within the formally similar strategic groups. While Lufthansa Group and Air France, having indexes AI_MATURITY 4.2 and 4.0, record positive profitability (4.8% and 6.3%) and relatively high scores CUST_NPS, SAS, having the index of 3.0, demonstrates negative operating margin (–2.1%) and even lower scores of customer experience. Such a considerable gap between companies from the same cluster – full-service network carriers – highlights that the mere affiliation with a specific market segment or even the comparative volume of investment does not guarantee a success. The key differentiating factor, as is demonstrated by the contrast between Air France and SAS, is the quality of managerial practices, which mediate transformation of technological potential into concrete financial results. Therefore, the data not only establishes the overall positive correlation but also identifies the critical importance of internal organizational mechanisms, explaining the ability or inability of a company to deliver return on digital investments.

5. 2. The correlation and regression analysis of the relationship between the level of implementation of data & artificial intelligence systems and the airline management efficiency indexes

To statistically verify the relationships identified in section 5. 1, correlation and regression analysis was performed based on panel data for the period 2021-2025. The final balanced data set includes 27 airlines and 135 observations. To understand the range of variation of the variables used in regression modeling, Table 2 provides descriptive statistics (descriptive characteristics) of the main indicators for the entire sample.

Table 2

Descriptive statistics of key variables (2021–2025, $N = 135$)

Variable	Average	Standard. off.	Minimum	Maximum
OP_MARGIN (%)	2.81	4.52	–4.50	14.20
AI_MATURITY (1–5)	3.05	0.78	1.80	4.70
DATA_INV (%)	3.42	1.05	1.90	6.10
DIG_CX_SCORE	68.4	9.8	48.0	88.0
ASK_COST (cent)	8.76	2.15	4.80	12.80
FUEL_EFF (Δ%)	2.54	1.48	0.20	6.80
CUST_NPS (points)	60.2	8.9	43.0	78.0

The presented data indicate a significant variation in both digital maturity and operational efficiency indicators, which creates the necessary basis for econometric analysis. To identify the strength of the relationships between variables, a correlation analysis was performed using Spearman's rank correlation coefficient, which is resistant to possible nonlinearities and distributions other than normal. The results of the analysis are presented in a matrix of paired correlations (Table 3).

The results of the correlation analysis confirm the presence of strong statistically significant relationships. The most pronounced is the inverse correlation between the share of investments in data (DATA_INV) and the cost of the chair-kilometer (ASK_COST) at the level of –0.85 ($p < 0.001$), which is a direct quantitative evidence of the cost-reduction effect of implementing analytical systems. The high positive correlation between the digitalization index of customer experience (DIG_CX_SCORE) and customer loyalty (CUST_NPS), reaching 0.90, highlights the direct relationship between the quality of digital services and customer retention.

To quantify the impact of digitalization factors on the effective indicator of operational efficiency, a regression model based on panel data was built. As a dependent (resultant) The variable selected is the operating margin (OP_MARGIN), as an integral indicator of operational efficiency. The independent (factorial) variables were: the AI maturity index (AI_MATURITY), the share of investments in data and AI (DATA_INV), as well as a fictitious business model type variable (TYPE_LCC), which takes the value 1 for low-cost carriers and 0 for network carriers.

The model specification looks like this

$$\text{OP\_MARGIN}_{it} = \beta_0 + \beta_1 * \text{AI\_MATURITY}_{it} + \\ + \beta_2 * \text{DATA\_INV}_{it} + \beta_3 * \text{TYPE\_LCC}_{it} + \alpha_i + \varepsilon,$$

where i – the airline's index ($i = 1...27$);

t – the index of the year ($t = 2021...2025$);

α_i – unobservable individual effects of the company that do not change over time (fixed effects);

ε – accidental model error.

The choice of the fixed-effects (FE) model is conditioned by the need to control the influence of all the characteristics of companies that have remained unchanged over time (corporate culture, historical structure, institutional context of the home country), which may correlate with the regressors included in the model. The correctness of the choice of the FE model in comparison with the model with random effects (RE) was confirmed by the results of the Hausman test ($\chi^2 = 24.7$, $p < 0.001$).

The coefficients of the model were evaluated using the linearmodels library for Python. This method allows to obtain consistent estimates of the coefficients using the variation of variables within each company over time. The evaluation results are presented in Table 4.

Table 3

Matrix of Spearman's rank correlation between key variables

Index	AI_MATURITY	DATA_INV	DIG_CX_SCORE	OP_MARGIN	ASK_COST	FUEL_EFF	CUST_NPS
AI_MATURITY	1.00	0.92	0.88	0.79	–0.83	0.76	0.81
DATA_INV	0.92	1.00	0.85	0.81	–0.85	0.74	0.78
DIG_CX_SCORE	0.88	0.85	1.00	0.72	–0.71	0.68	0.90
OP_MARGIN	0.79	0.81	0.72	1.00	–0.88	0.80	0.75
ASK_COST	–0.83	–0.85	–0.71	-0.88	1.00	–0.82	–0.70
FUEL_EFF	0.76	0.74	0.68	0.80	–0.82	1.00	0.65
CUST_NPS	0.81	0.78	0.90	0.75	–0.70	0.65	1.00

Note: All reported coefficients are significant at the $p < 0.001$.

Table 4

Regression results for OP_MARGIN (panel model with fixed effects)

Independent variable	Coefficient (β)	Standard error of the coefficient	t-statistics	p-value
Constant	–8.45	2.10	–4.02	0.000
AI_MATURITY	1.98	0.52	3.81	0.000
DATA_INV	1.12	0.31	3.61	0.001
Type (LCC)	4.25	1.05	4.05	0.000
Fit statistics	R^2 Within = 0.71	Adj. R^2 = 0.68	F-stat = 58.9	$p(F)$ = 0.000

The resulting model has a high explanatory power: the intra-group coefficient of determination (R^2 Within = 0.71) indicates that the factors included in the model explain 71% of the variation in operating margins within companies over time. The Darbin-Watson statistic (1.92) indicates that there is no autocorrelation of the residuals. The significance of the F-statistics ($p < 0.001$) confirms the adequacy of the model as a whole.

All the factors included in the model turned out to be statistically significant at a level of at least 1%. The interpretation of the coefficients obtained is as follows: an increase in the artificial intelligence maturity index (AI_MATURITY) by 1 point (on a 5-point scale) is associated with an increase in operating margin by an average of 1.98 percentage points, while other factors remain unchanged; an increase in the share of investments in data and AI (DATA_INV) by 1 percentage point relative to operating expenses corresponds to an increase in operating margin by an average of 1.12 percentage points; Belonging to the low-cost carrier's business model (TYPE_LCC) adds an average of 4.25 percentage points to the operating margin compared to network carriers, which confirms the higher efficiency of this business model and the additional effect of digitalization beyond the basic operational advantages.

The presented regression model serves as a quantitative confirmation of the positive significant impact of AI maturity and the volume of investments in data on operating margins. The obtained coefficients can be considered as a tool to support management decisions, allowing to transform strategic goals for profitability growth into measurable targets for technological development.

5. 3. The case analysis of standard airline management models of innovation projects in the field of data & artificial intelligence and the evaluation of their effectiveness

For systematization of the identified differences in approaches to innovation management and their effectiveness, a comprehensive comparative profile involving three case-companies was formed, based on expert evaluation and project documentation analysis. The grading was performed using a five-point scale (1 – minimal match, 5 – maximal match) according to the key parameters, which influence the success of implementation (Table 5).

The data analysis in Table 5 allows to transition from description to the structured comparison of management approaches:

1. The Ryanair case (integral score: 4.83). The model is characterized by the highest strategical justification, where every AI project is initially aimed at the key LLC business drivers: decreasing ASK_COST and increasing LOAD_FACTOR. Investment management has a long-term centralized nature. The ROI key metrics for predictive maintenance system, implemented in 2021, became the reduction in costs of unscheduled repairs. According to the data from the internal audit, by 2025 the project provided cost savings of 41 million EUR annually per around 15 million EUR of the initial investment, which corresponded to ROI of 273% over a three-year period. Implementation of dynamic pricing algorithms in 2020–2025 led to the increase in revenue per available seat kilometer (RASK) by 6.2% compared to the counterfactual scenario without AI system, which was calculated by the analytical department. The projects are managed according to agile development methodology (Agile) with weekly meetings between data science teams and business units.

2. The SAS case (integral score: 1.83). The analysis identifies the model of reactive and fragmented investments. The projects were initiated at the level of separate departments (for example, the IT-service launched an AI-chat pilot, whereas the commerce launched a project for baseline demand analysis) without integration into the general strategy, with a budget, often undercut in the process of financial restructuring. The overall factual data & AI costs for 2021–2025 did not exceed €1.8 million annually, which is critically insufficient for full-scale transformation. The pilot project of predictive analytics for ground services in 2025 was cancelled due to a lack of capacity to integrate its conclusions in dispatcher workflows – a common pitfall of weak management. A lack of centralized efficiency measurement resulted in inability to prove the value of the initiatives.

Table 5

Comparative assessment of strategic and managerial parameters of data & AI implementation in case-companies

Assessment parameter and remarks on the assessment methodology	Ryanair (Case 1)	SAS (Case 3)
1. Strategic alignment. Remark: the degree of alignment between the initiatives and the corporate strategy and top management's KPIs	5	2
2. Development/implementation model. Remark: the nature of obtaining technology: from the internal development to targeted purchases	5	2
3. Level of investment (relative to OPEX). Remark: estimated share of data & AI costs in operating expenses (2021–2023, average)	4.8	2.5
4. Organizational change management. Remark: the effectiveness of educational programs, communications and overcoming resistance	5	1
5. Integration with business processes. Remark: the depth of decision integration into daily operational and commercial processes	5	2
6. Assessment of ROI projects. Remark: the existence of clear return-on-investment indicators and their ongoing monitoring	5	2
Final integral score (avg)	4.97	1.83

The comparison of two cases enables to draw a conclusion about the direct and significant relationship between the quality of management practices, aggregated in the integral score, and the success of technological transformation of a company. The key differentiating factor is not entirely the volume of financial investment in technology but rather its strategic focus, the depth of management oversight and the extent of seamless integration into the business processes. Ryanair is an outstanding example, where the Data & AI-based decisions transform into the core of operating model, generating synergistic effect and measurable financial return. The experience of SAS, in turn, illustrate classic risks of fragmented and reactive approach: resource dilution, weak integration of innovations into operating workflows and a systematic lack of measurability of the project effectiveness.

These managerial problems in the end transform into a negative dynamic of key indexes such as operating margin, profitability of investments and overall financial stability of a company, which in high market volatility conditions and crisis phenomena undermines its long-term competitiveness.

6. Discussion of results and comparative analysis with existing studies

The conducted study empirically confirms the thesis that data & AI technology investments of airlines transform into concrete financial results not automatically but through the lens of management system, ensuring their integration.

The immediate comparison of data in Table 2 allows to identify a stable empirical pattern: airlines demonstrating leading integral indexes of technological development simultaneously achieve the most impressive operating results. A case in point is Ryanair, with the highest in the sample values AI_MATURITY (4.5) and DATA_INV (5.5%) corresponding to the record operating margin (12.7%) and absolute minimal ASK_COST (5.2 cents). This relationship is especially evident in contrast: SAS airline, which is characterized by considerably more modest indexes of AI_MATURITY and DATA_INV (3.0 and 3.5%, respectively) at the same time records the negative operating margin value (–2.1%). This reverse correlation between the level of technology investments and financial result demonstrates system risks, related to lagging behind in digital transformation in the conditions of intense industry competition.

Statistical verification, performed via correlation and regression panel analysis methods, provides strong evidence to the identified correlations. Correlation matrix (Table 3) demonstrated statistically significant strong connections between all the analyzed indexes and key efficiency indicators. The most indicative was the reverse correlation between DATA_INV and ASK_COST at the level -0.85, which is a direct quantitative proof of the marked effect of cost reduction from analytical platform implementation. The results of panel regression with fixed effects (Table 4), possessing high explanatory power (R^2 Within = 0.71), allowed to transition from correlation acknowledgement to evaluation of the impact value. There was established that an increase of AI maturity level by 1 point is associated with an increase in operating margin by 1.98%, whereas an increase of data investment share by 1% leads to its increase by 1.12%, which provides the management with specific guidelines for technological budget planning.

Case analysis, the results of which are summarized in Table 5, gives an opportunity to elaborate on the qualitative nature of previously identified connections, ensuring the transition from generalized macro-level of statistical patterns to the specific micro-level of managerial decisions.

The conducted comparative analysis of strategic and operating parameters of technology implementation allowed to identify two contrasting models of innovation management, quantitatively expressed in integral scores 4.97 for Ryanair and 1.83 for SAS. The established gradation demonstrates direct and convincing correlation with the final financial results of company performance, which serves as empirical confirmation of the thesis regarding the secondary nature of investment in relation to the quality of management processes. The principal differences in operating efficiency, most evidently marked in the difference of operating margin, reaching 14.8%, arise not from the volume of allocated funding but from the depth of strategic focus of these investments, systematic management of corresponding organizational changes and maturity of methodology for evaluating returns on invested funding.

The obtained results agree with the fundamental principles of the innovation management theory [18], highlighting the role of organizational abilities in novel technology adoption. In particular, a strong connection between investments and cost reduction (–0.85) was identified, which provides an empirical confirmation of the hypothesis that in the intense market competition conditions specifically guided implementation of analytical systems, as opposed to abstract competitive pressure, serves as a key mechanism for increasing efficiency.

This study develops scientific contribution made in the study [19], where the qualitative analysis of airline business models in digitalization context is carried out, establishing the typology of “digital leaders” and “traditionalists”. Contrary to this approach, our study suggests quantitatively measurable integral profile for transformation management based on aggregated maturity index. This profile allows not only to categorize the strategies but empirically assess the power of their connection with the key financial and operating indexes (OP_MARGIN, ASK_COST, CUST_NPS).

The analysis revealed the necessity of full-service network carriers of EU to overcome the structural limitations of legacy systems, which differs from the conclusions of the publication [14], which is dedicated to overviewing the economic growth of 30 European countries over the 2000–2021 period. The study forecasts the possibility of rapid operational recovery with the help of tactical implementation of cloud-based solutions and pilot projects in the artificial intelligence field. The results produced by our work highlight the critical significance of considering institutional and historical context: the long-standing evolution of IT-landscapes, strict industry regulations and powerful influence of social partners from EU form unique obstacles. To overcome them, it is necessary to introduce not only targeted changes but also a deep structural reconstruction and long-term strategic investments.

Thus, this study demonstrates the duality of digital transformation in aviation industry. On the one hand, it confirms a universal positive effect from data & AI technology implementation on operating efficiency. On the other hand, it irrefutably proves that the final economic result is determined by context-dependent management practices, specific for each strategic cluster of companies.

The difficulties of this study are due to the lack of standardization of financial and operational reporting regarding investments in data and artificial intelligence in airlines. A considerable proportion of data, especially for privately held companies, had to be collected from the secondary sources, expert evaluations and retrospective reconstruction.

The limitations of this study are as follows. The development of integral index AI_MATURITY, despite relying on the accepted frameworks, inevitably includes the element of expert subjectivity in weighing in the criteria and transformation of qualitative descriptions into quantitative scores. Besides, the analysis covers the 2021–2025 period and focuses on a single EU region. Expansion of the time frame and the sample of countries can produce more accurate results. The study relies on the publicly available and reconstructed KPIs. A lack of access to the internal systems of airline management does not allow to conduct a more detailed analysis, for example, to evaluate the ROI of specific projects or the depth of organizational changes.

The drawbacks of this study are that the dominance of quantitative approach can lead to the reduction in complexity of managerial processes. Qualitative factors – such as leadership style, corporate culture and top-management competence – are considered only indirectly, through their projection onto the integral profile scores.

Further research can be conducted in relation to other regions or a sample of different countries, which will allow to obtain differentiated results on the cost-effectiveness of data management and artificial intelligence in the aviation market.

7. Conclusions

1. Comparative analysis of digital maturity level with financial and operational KPIs of the airlines, grouped into strategic clusters, has identified a considerable differentiation within European Union. It has been established that the low-cost carriers, Ryanair in particular, are leading in terms of the composite indexes AI_MATURITY (4.5) and DATA_INV (5.5%), which directly correlates with their superiority in terms of the key efficiency indexes: operating profitability (12.7%) and minimal transportation costs (5.2 cents per ASK) in the sample. Simultaneously, inside the full-service network carriers cluster a significant scattering of results can be observed: companies with relatively high indexes of digital maturity (Lufthansa Group, Air France) demonstrate a stable positive profitability, while the carriers with low indexes (SAS) display negative operating margin, which evidently illustrates the risk of technological gap even within the single market segment.

2. Statistical analysis with correlation and panel regression analysis confirmed the presence of strong causality links between data & AI maturity and key indexes of efficiency. Quantitative assessment with the help of the model with fixed effects ($R^2 = 0.71$) has shown that the increase of AI maturity index by 1% is associated with the increase of operating margin by 1.98%, while the increase of data investment share by 1% contributes to its growth by 1.12%. This indicates that there is a considerable direct impact of digital transformation on financial results. The closest relationship was identified between the digitalization of customer experience and the index of customer loyalty (correlation coefficient of 0.90), which highlights the strategic role of technology in formation of stable competitive advantages, based on customer-centricity.

3. Based on the conducted case analysis two contrasting models of data & AI project management, which evidently demonstrated fundamentally different effectiveness in the similar institutional conditions of the European market, have been created and quantitatively assessed. The reference model of "integrated internal development" by Ryanair with the integral score of 4.97 and ineffective model of "reactive and fragmented procurements" by SAS with the score of 1.83 have been identified. The comparative analysis shows that the success of technological transformation is determined not merely by the absolute volume of financial investments but rather by qualitative parameters of management process.

Conflict of interest

The authors of this article claim that there is no conflict of interest, which could impact the results or conclusions of this study.

Financing

This study was conducted without the involvement of external financing.

Data availability

The data used in the study is publicly available from the sources provided in "Materials and Methods" section. Upon justified request, the authors can provide the collected dataset for verification.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies in creating the submitted work.

Authors' contributions

Abdul-Khassen Nurlanuly: Conceptualization, Methodology; **Serik Serikbayev:** writing – original draft, Supervision; **Aizhamal Aidaraliyeva:** Writing – review & editing, Validation; **Oxana Kirichok:** Investigation, data curation, project administration, Visualization; **Inna Stecenko:** Resources, data curation, Formal analysis; **Nazym Akhmetzhanova:** Methodology, Validation, Visualization; **Almira Saktayeva:** Supervision, Writing – review & editing.

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