ETELKA ÉVA KATITS – JUDIT KATALIN FEJES

THE ROLE OF DOUBLE AI IN SMART TOURISM – CORPORATE STRATEGIES SERVING RISK RESILIENCE

A KETTŐS MI SZEREPE AZ OKOS TURIZMUSBAN – VÁLLALATI STRATÉGIÁK A KOCKÁZATI REZILIENCIA SZOLGÁLATÁBAN

The study examines, within the framework of smart tourism, "double AI" (AI-on-AI) systems. The aim is to present how leaders in the tourism sector (SMEs, municipalities, destinations) can use these new frameworks to increase risk resilience. The research is grounded in the theoretical frameworks of resilience and AI technology, utilising both qualitative (case studies) and quantitative (surveys) methods. According to the literature, AI enables personalised services and enhanced efficiency in tourism while also presenting new challenges related to data protection and employment. The study complements this by presenting international and Hungarian examples, as well as three comparative case studies. The results encompass, on the one hand, the primary components and impacts of AI systems on resilience, and, on the other hand, the key quantitative indicators from the surveys. This mixed-method approach supports corporate leaders' decision-making from several perspectives.

Keywords: **double AI, resilience, risk management, smart tourism, SME**

A tanulmány az intelligens turizmus keretében vizsgálja a „kettős MI" (AI-on-AI) rendszereket. A cél annak bemutatása, hogy a turisztikai ágazat vezetői (KKV-k, önkormányzatok, desztinációk) hogyan használhatják ezeket az új keretrendszereket a kockázatokkal szembeni ellenálló képesség (reziliencia) növelésére. A kutatás az ellenálló képesség és az MI-technológia elméleti keretrendszerére épül, kvalitatív (esettanulmányokat) és kvantitatív módszereket (felméréseket) egyaránt alkalmazva. A szakirodalom szerint az MI személyre szabott szolgáltatásokhoz és a turizmus hatékonyságának javulásához vezet, miközben új kihívásokat is jelent az adatvédelem és a foglalkoztatás terén. A tanulmány ezt kiegészíti nemzetközi és magyar példák és három összehasonlító esettanulmány bemutatásával. Az eredmények egyrészt az MI-rendszerek ellenálló képességre gyakorolt főbb összetevőit és hatásait, másrészt a felmérésekből származó legfontosabb mennyiségi mutatókat foglalják magukban. Ez a vegyes módszerű megközelítés több szempontból is támogatja a vállalati vezetők döntéshozatalát.

Kulcsszavak: **okos turizmus, kettős MI, reziliencia, kockázatmenedzsment, KKV**

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The digital transformation of tourism has ushered in a new era, in which *Artificial Intelligence* (AI) is a strategic tool for risk management. During the transformation of tourism, AI has become an increasingly important factor. AI applications are involved not only in personalising travel experiences (through recommendation systems and chatbots) but also in automating and optimising operational processes (Siddik et al., 2024; OECDa, 2024). However, the degree of adaptation in the sector is uneven: according to OECD data, in 2023, only 11% of tourism intermediaries and 4% of hotels in Europe used some AI solution (OECDa, 2024). In contrast, recent research highlights that AI plays a crucial role in enhancing the efficiency of tourism and achieving sustainability goals (Siddik et al., 2024). Nevertheless, many small businesses, especially Hungarian SMEs, are falling behind in technological developments (OECDa, 2024) – thus, it is essential to develop practical guidelines for them.

In this study, we introduce the concept of „double AI" (AI-on-AI) as an technological framework for smart tourism. We interpret this as a collective term for hierarchically organised AI systems, in which an algorithm functions not only as a data processor but also as the supervisor and optimiser of another AI system. For example, one AI can forecast expected tourist traffic, while another AI continuously evaluates the accuracy of these forecasts and adjusts the strategy accordingly. With such a system, companies can respond more quickly to unexpected events (such as sudden fluctuations in demand or natural disasters), thereby increasing their crisis resilience.

Research Topic and Relevance

The literature addresses various AI-based applications in tourism (e.g., personalised recommendation systems, chatbots, and demand forecasting). However, it rarely examines the integrated, corporate-level strategic application of AI to strengthen resilience. This knowledge gap forms the basis of the research question: How can the"dual AI" concept be realised in tourism companies to increase their risk resilience?

In terms of realising tourism's sustainability and social goals, risk management is significant, considering the increasing impact of climate change, economic fluctuations, and other unexpected shocks. Reichstein et al. (2025) emphasise that AI-based, integrated *Early Warning Systems* (EWS) are vital for forecasting and managing climate and natural risks. In this light, the relevance of this research lies in the fact that, with the help of AI, we link the development of innovatstrategy and risk management, thus facilitating the long-term resilience and competitiveness of tourism enterprises.

Research Objectives

The primary goal of this research is to develop a comprehensive framework and practical guide that supports the development of dual AI-based solutions applicable in the tourism sector. Specifically, we examine how AI-based predictive models and decision-support simulation models can be integrated into corporate strategy and how they can simultaneously contribute to strengthening corporate resilience.

To achieve this goal, the research

- maps the applicability of AI-based EWS (AI-EWS) for identifying and mitigating tourism risks,
- examines how dual AI systems increase the accuracy of financial and demand forecasts and support strategic decision-making,
- evaluates the socio-economic impacts of the most modern tourism technologies (e.g., AI, *Internet of Things* (IoT), Big Data, digital platforms, smart infrastructure), with special focus on local community involvement and sustainability.

The research also aims to provide practical guidance on how corporate strategies can simultaneously strengthen the digitalization and resilience of the tourism sector.

Research Questions

To precisely define the focus of the research, we seek answers to the following two research questions:

1. How does the integration of dual AI systems in smart tourism increase the predictive and adaptive capabilities of decision-making?
2. How does dual AI-EWS contribute to aligning corporate resilience and sustainability goals?

The novelty of the research lies in its representation of an integrated, system-based approach, in contrast to existing fragmented AI applications that consider not only technological but also strategic and social aspects. The developed framework can serve as a practical guide for tourism stakeholders, helping organisations connect AI technology and resilience, all in the service of sustainable development goals.

Historical and Literature Review of Intelligent Resilience Management Framework

The literature review was conducted with PRISMA-like transparency (SPAR-4-SLR protocol) (Wang et al., 2025).

The *Intelligent Resilience Management* (IRM) framework is based on the coordinated integration of several interrelated scientific domains. Here, we explore how the seven components of the IRM framework are reflected in the academic literature (*Figure 1*).

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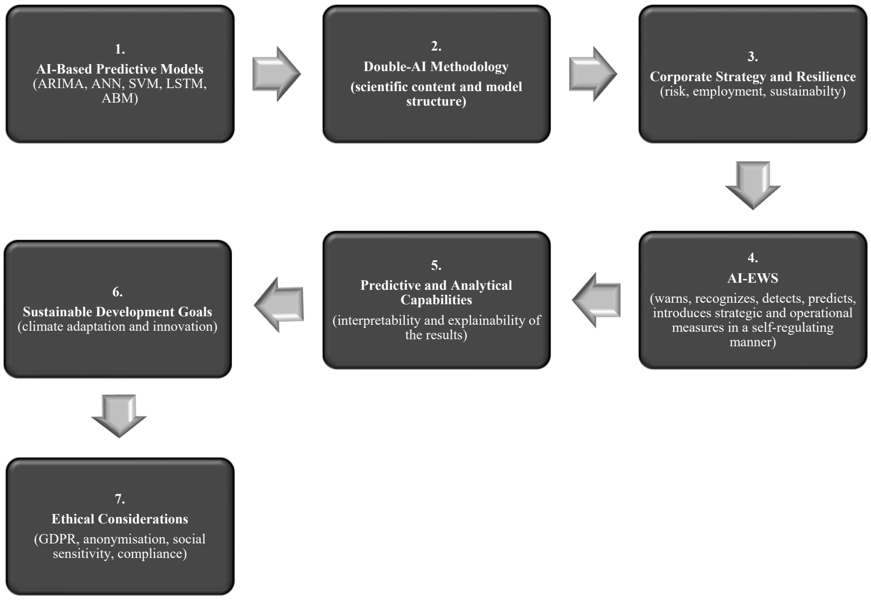
Figure 1

The IRM Framework



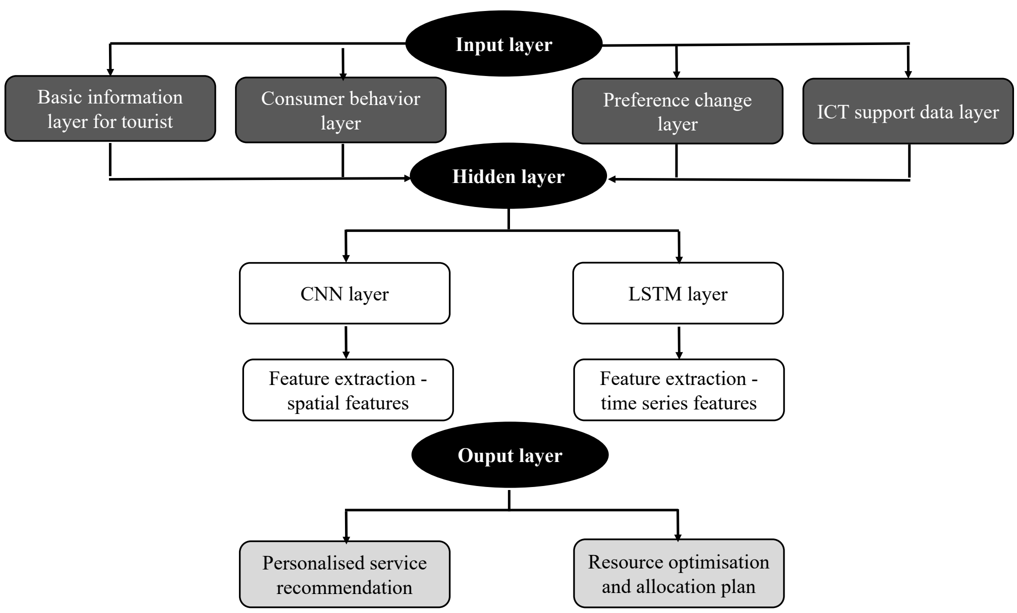
Source: author's compilation (2025)

1. AI-Based Predictive Models

The history of tourism forecasting and modelling dates back to the 1970s and 1980s, when classic time-series models (e.g., ARIMA = *AutoRegressive Integrated Moving Average*) were used to predict guest flows. In parallel with the development of IT from the 2000s onwards, more and more AI algorithms (*Artificial Neural Networks*=ANN, *Support Vector Machines* (SVM), and deep networks) have been applied to the analysis of tourism data (Song & Zhang, 2025), as reported on frontiersin.org. In the 2010s, neural networks based on long-term memory (e.g., LSTM=*Long Short-Term Memory*) gained popularity for capturing temporal dependencies (Song & Zhang, 2025) at frontiersin.org. At the same time, in the financial sector, especially in risk analysis and planning, simulation methods (Monte Carlo), as well as *Agent-Based Modelling* (ABM), have been used for a long time. Agent-based simulation has also been applied in tourism for studying visitor behaviour and spatial interactions (Wallinger et al., 2023). The post-COVID-19 recovery demonstrates the robustness of tourist flows: by 2023, global tourism had significantly rebounded to 2019 levels (WTTC, 2024). However, economic and climate crises have brought new,

Figure 2

Example of a Neural Network Architecture for Tourism Purposes



Source: author's compilation based on Tian & Tang (2025, p. 4) unforeseen challenges that can be examined using complex AI-based and simulation tools. Recent research, for example, shows that AI-based predictive systems (such as LSTM) are effective for analysing the environmental impacts of tourism and capturing long-term dependencies (Song & Zhang, 2025).

The application of AI in tourism and financial analyses has steadily expanded over the past decades. Initially, traditional tools for temporal forecasting, such as ARIMA models, gained widespread adoption. Zhang et al. (2018) pointed out that ARIMA (and ARCH/GARCH) models are fast, convenient, and relatively accurate for analysing economic time series. However, these are increasingly being supplemented or replaced by *Machine Learning* (ML) solutions. For example, ANN and deep learning methods have become effective forecasting tools. Tian & Tang (2025) developed an ANN model that processes large datasets to predict tourism behavioural patterns, showing a significant increase in accuracy compared to traditional statistical methods (nature.com). The flexibility of ANNs makes them suitable for recognising complex patterns, which is well utilised in forecasting tourist flows.

Figure 2 illustrates the structure of a typical tourism ANN model, where various tourist information (demographics, consumption patterns) enters the input layer. CNN and LSTM units are present in the hidden layer, and the output layer returns personalised service recommendations and optimised resources.

SVMs gained widespread use in the early 2000s for nonlinear time series analysis. Pai et al. (2005) developed a multinational SVM model for forecasting tourism demand and found that their hybrid SVM-neural network solution outperformed previous forecasting methods. This shows that SVMs are also effective in handling complex influencing factors.

LSTM networks are capable of modelling long-range temporal dependencies and have therefore been widely used in recent years for tourism and economic forecasting. Zhang et al. (2025), for example, used a hybrid of BiLSTM (*Bidirectional LSTM*) and Transformer networks to accurately capture both short-term fluctuations and long-term trends, outperforming an ARIMA-based method. This indicates that deep networks are increasingly replacing classical approaches in the era of large databases.

In the field of uncertainty and risk analysis, the Monte Carlo method has long been a fundamental tool. For instance, Zakhary et al. (2009) used a Monte Carlo simulation to model a hotel's booking process, simulating booking events and cancellations for the entire forecasting period. With this method, they obtained survival distributions and modelling densities for the expected number of guest nights. As noted, the Monte Carlo approach methodologically surpasses other techniques, as it can vary all sources of uncertainty simultaneously and does not require parametric assumptions.

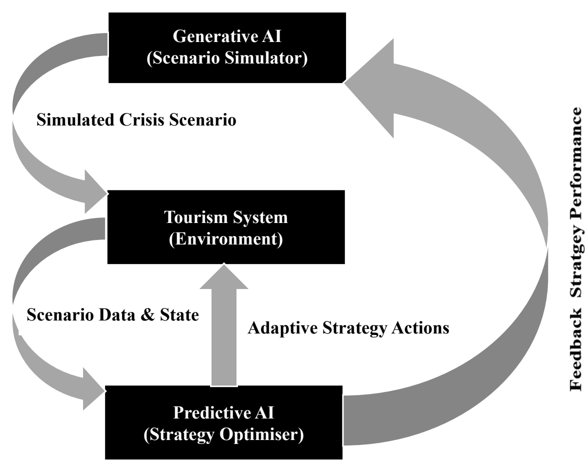
The ABM method simulates the interactions and behaviours of autonomous "agents" (e.g., tourists, residents, entrepreneurs). Agent-based modelling enables the representation of the complex tourism system, where the heterogeneity of individuals, their interactions, and non-linear processes can be effectively captured. Nicholls et al. (2016) emphasise that ABM can manage the assumptions (homogeneity, linearity, equilibrium, rationality) that traditional models typically require, thus making it particularly useful for simulating complex tourism systems (planning, development, marketing).

2. Double-AI Methodology

A dual AI system consists of two AI components (*Figure 3* in a tourism decision support system): (1) a generative module that simulates crisis scenarios (on the left), which are tested in a tourism decision environment., and (2) a predictive optimisation module then proposes optimal responses (e.g., strategies) for the given situation (on the right), and applying these makes the effects of the decisions visible in the tourism system. The feedback loop (dashed arrow) indicates that the generative model can learn from the outcome of the strategy – for example, after recognising an effective response strategy, it can generate new, different crises for further testing by the system. The coordinated functioning of these two layers determines the system's effectiveness; therefore, it is necessary to describe their interaction using formal logic.

Figure 3

Schematic Operational Outline of a Dual AI System Based on Synthetic Data



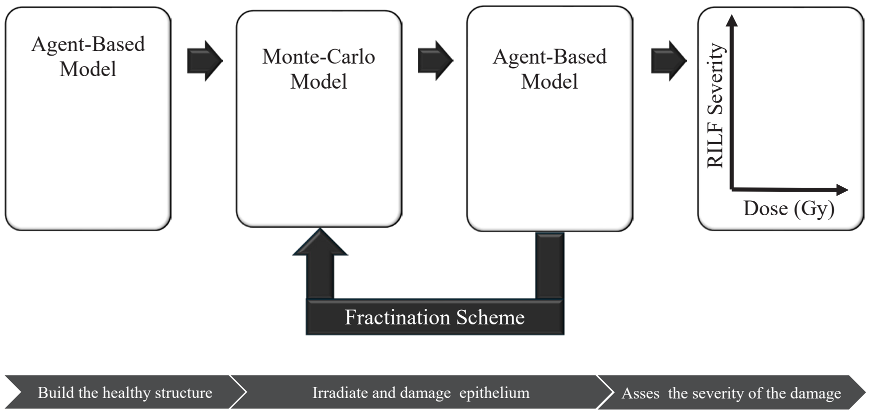
Source: author's compilation (2025)

The dual AI architecture implements a dual AI process: a first, predictive model forecasts tourism indicators (e.g., demand, visitor numbers), and then a second, simulation model examines the dynamics of the region or system based on these forecasts (Cogno et al., 2024). For example, one model (Time Series AI) may use an LSTM or ARIMA network to predict guest traffic based on historical data, after which a so-called Monte Carlo or ABM simulation is fed from these forecasted data.

Figure 4 presents a schematic model showing how the ABM and Monte Carlo modules cycle the system's state: the ABM creates the structure, and after a Monte Carlo irradiation or external-effect simulation, feedback is provided for the system's next step (Cogno et al., 2024).

Figure 4

The ABM and Monte Carlo Modules



Source: author's compilation based on Cogno et al. (2024, p. 5)

The essence of the Dual AI approach is that, by combining ML and simulation techniques, we can test complex scenarios and assess risk impacts, increasing the model's flexibility and realism.

In the game-theoretical model, the generative and predictive AI can be seen as two "players" with opposing goals, who together produce an outcome. Generative AI can generate "worst-case" crises – acting as an adversary to the system – while the goal of predictive AI is to minimise such damage, acting as a defender (similar to the minimax optimisation principle). The approach is related to the Stackelberg game concept: the crisis generator, acting as the "leader," moves first by presenting a scenario, while the "follower" (the response-strategy AI) makes its optimal decision with this knowledge (Kar et al., 2018).

In the Bayesian approach, the generator is modelled less as an adversary and more as a source of uncertainty. Here, the generative AI explores many possible future states, effectively providing a prior distribution over crisis events. The task of predictive AI is to manage this uncertainty: using Bayes' theorem, it updates probabilities as new information arrives (e.g., the first signs of a crisis), or performs stochastic optimisation that accounts for the likelihood of various scenarios. The Bayesian-based dual AI model, therefore, seeks to maximise expected utility.

The methodological elements include the classic ARIMA model, which builds on linear time-series models and works well when the data (or their differenced versions) are stationary. ARIMA components combine past values and random errors. However, ARIMA is only sensitive to linear relationships; it does not handle complex nonlinear trends and long-term dependencies well (Zhang et al., 2025), which can be limiting for tourism data.

In contrast, LSTM networks are suitable for learning complex temporal patterns. They retain important information over time, enabling them to effectively track nonlinear and long-term trends (Song & Zhang, 2025). Recently, more hybrid solutions have emerged: for example, Zheng and Zhang (2023) presented a GM–LSTM model in which a grey model captures the general trend in the data, while the LSTM learns the nonlinear fluctuations in the residuals.

Monte Carlo simulation uses an entirely different approach: by repeated random sampling, we simulate many "what if…" scenarios (Pavlik & Michalski, 2025). According to Pavlik and Michalski (2025), Monte Carlo simulation is an advanced statistical tool for forecasting risk management, often used to assess the profitability of financial projects and analyse risks. The great advantage of the method is that, when analytical solutions become too complex, Monte Carlo can provide numerical results. For example, Sun et al. (2024) calculated a 99% probability range for global tourism CO_2 emissions using a Monte Carlo simulation, thereby obtaining a quasi-confidence interval for the forecast.

ABM simulates the behaviour and interactions of individual "agents" (tourists, businesses, destination managers, etc.) in complex systems. In tourism, where the heterogeneous preferences and behaviours of individual decision-makers are crucial, ABM is well-suited to analysing what-if scenarios (Wallinger et al., 2023). In the ABM framework, each agent operates according to a set of rules (e.g., budget constraint, risk perception). Thus, complex, emergent system dynamics can develop (tourists' spatial distribution, crowding, demand changes). In tourism, ABM is often used for traffic management and crisis response. Luo et al. (2021) developed a NetLogo-based ABM to examine post-COVID tourism market recovery, modelling the market's restoration by accounting for individual tourist decisions and destination strategies.

3. Corporate Strategy and Resilience

Based on a content analysis of definitions of resilience across different disciplines, a common interpretation of the behaviour of resilient systems is presented, which can be described by terms such as adaptation, retrieval, performance, absorption, retention, confrontation, return, response, and resistance (Zahedi et al., 2023).

Building on the General Systems Theory, corporate resilience theory includes inputs of human resources, socio-cultural values, institutional settings, and social and environmental issues, enabling organisational structure, value and belief subsystem, resilience mindset, sustainability practices, adaptive and buffering capacities, and sustainability performance as the output (Kantabutra & Ketprapakorn, 2021).

Corporate strategy directs attention to what environments to operate in. Part of the corporate strategic management process is ensuring that companies have adequate resilience. According to Zahedi et. al. (2023), three factors contribute to organisational resilience:

1. resilience is the function of an organisation,
2. resilience resulting from organisational operations (namely, an action done by an organisation),
3. resilience is a metric of anomalies that an organisation can tolerate.

Ruiz-Martín (2018) believes that all these definitions have the same meaning and refer to the organisation's survival in the face of shocks and risks. Risk is the threat, and resilience is the response to that threat.

The international standard for risk resilience is ISO 31000, which provides a framework for risk management (financial, operational, strategic, IT risks, cybersecurity, and compliance) that all organisations can adapt. The basic principles of ISO 31000 include the identification, assessment and ongoing management of risks, as well as the integration of risk management at all levels of the organisation. According to the ISO 31000 approach, AI technologies (e.g. dual AI-based predictive models) can play a key role in the continuous cycle of risk management (planning, execution, monitoring, improvement) in predicting threats and automating risk management (TechTarget, 2025).

Here, we mention the RISKRES (*RISK-RESilience*) model, which addresses risk analysis and the development of resilient strategies together (Singh, 2022).

4. AI-EWS

For tourism enterprises, timely risk detection is crucial: pandemics, extreme weather events, and geopolitical crises all require rapid responses. AI-based EWS systems can assist in this by continuously monitoring and analysing large amounts of data (climate data, transport conditions, health statistics, etc.). According to the international organisation WMO (2025), such AI-based EWSs are becoming "life-saving tools" for supporting sustainable development.

In the tourism context, Ghaderi et al. (2024) examined the resilience of smart tourism destinations from a cybersecurity perspective. Their study found that the interconnectivity and decentralised operation of smart destinations enhance defensive capabilities, while also highlighting the importance of risk management measures such as encryption, regular backups, incident management protocols, and awareness-raising programs. Furthermore, the OECD (2024) points out that integrating AI-based warning and decision-support tools can increase the tourism sector's resilience to external shocks (e.g., climate change, pandemics).

In dual AI systems, for example, one AI agent may be responsible for continuously monitoring data and predicting threats (e.g., regulatory models based on climatological or epidemiological data). In contrast, the other model performs strategic simulations, proposing alternative response measures for company management. Such structures aim to ensure that responses to risks are faster, more adaptive, and comprehensive, thereby increasing corporate resilience.

5. Predictive and Analytical Capabilities

The performance of the double AI system can be evaluated by measuring the prediction accuracy and risks. The dual AI system developed in the research contains two modules.

AI1 – predictive module: regression and time series models (XGBoostt=*eXtreme Gradient Boosting*, LSTM). The output of the predictive model usually appears as future values or growth paths. It is essential to thoroughly validate models: the available data is divided into training, validation, and test sets, and cross-validation methods are employed to prevent overfitting. The leading indicators characterising model accuracy include *Root Mean Square Error* (RMSE) measures the spread of predictions, *Mean Absolute Error* (MAE) measures the magnitude of error, *Mean Absolute Percentage Error* (MAPE) gives the percentage error of the forecast, and the coefficient of determination, also known as explained variance (R^2) indicates how well the model captures the fluctuations of the target variable (Zhang et al., 2025). When assessing a model's acceptability or comparing two models, these indicators are critical: the lower the RMSE/MAE and the higher the R^2, the more accurate the estimate.

When measuring accuracy, it is worth examining the system's performance separately in calm periods and during crisis scenarios. Ideally, the double AI improves accuracy in both calm periods and crisis scenarios by training on the generated stress-test data. This is supported by the fact that some forecasting models have become more robust and produce less error by incorporating synthetic data (Chatterjee & Byun, 2023). It is also important to measure the actual positive rate and the true negative rate (interventions for minor fluctuations, which are overreactions).

Overall, if the accuracy of forecasts improves, volatility and potential loss decrease, and all this is coupled with greater profitability, then the system is both methodologically sound and commercially justified.

AI2 – generative-simulation module: it uses AI1's predictions to perform scenario analysis, exploring possible outcomes and optimal responses at the system level. The development of this module is supported by the Monte Carlo simulation technique, supplemented as necessary by ABM to illustrate the interactions of tourism actors.

We analyze quantitative data in SPSS and Python, and use the SMESBJ (*Small Medium Enterprises Smart Business Journey*) smart application (Katits, 2024).

The ROC (*Receiver Operating Characteristic*) curve and AUC (*Area Under Curve*) values are reliable and standardised measures of predictive model performance.

The ROC curve plots the relationship between the actual positive rate (sensitivity) and the false positive rate (1-specificity) across different thresholds. The AUC represents the area under the ROC curve and serves as a numerical indicator of the model's overall performance. An AUC value close to 1 indicates excellent predictive ability (Bradley, 1997; Huang et al., 2020; Muschelli, 2019), meaning that double AI predictive algorithms provide significantly reliable decision support in the context of smart tourism and regional employment (Fawcett, 2006).

The interpretability of model results is enabled by the principles of Explainable AI (XAI), thereby increasing transparency for decision-makers. To this end, for the AI1 module, the SHAP (*Shapley Additive exPlanations*) method calculates the contribution of each input feature to each forecast. Each variable is assigned a SHAP value, indicating the extent to which the given feature positively or negatively influenced the model output. This makes it possible to reveal which factors increase the risk the most in a given scenario.

Modelling is often based on limited or incomplete real data. Therefore, tourism research uses synthetic data (typically generated by generative models or theoretical distributions, e.g., simulated traveller demand models) to expand the training dataset. However, synthetic data is most appropriate for preliminary research (e.g., hypothesis testing, model training), while primary studies – if possible – should verify their results with real data. During validation, the distribution of generated data is compared with real data or known standards; for example, agreement is checked in network distributions, medians, or correlation structures. Care is also taken to ensure that AI-generated synthetic training data do not reinforce erroneous patterns, and that the model's generalizability is maintained.

Viglia et al. (2024) note that synthetic data are most useful in preliminary, experimental phases (such as pre-testing for validation). However, using synthetic data requires thorough model validation: predictive accuracy must always be compared with real, international benchmarks.

6. Sustainable Development Goals

Several SDGs are directly related to IRM's focus on tourism development, making AI a fundamental role in achieving them. According to the analysis by Vinuesa et al. (2020), AI can contribute to 134 of the 169 targets across the 17 SDGs – although it may also have negative impacts if ethical considerations are not embedded.

The most significant tourist potential lies in the goals of SDG 11 (Sustainable Cities), SDG 13 (Climate Action), and SDG 7 (Affordable and Clean Energy). Accordingly, IRM deploys AI solutions that account for environmental impact, social consequences, and SDG alignment.

7. Ethical Considerations

Data collection will be conducted using GDPR-compliant procedures, including anonymisation of personal data, documentation of consent forms, and consideration of social sensitivity considerations in the pilot region. A separate XAI and ethical compliance protocol will be implemented for AI models.

Research Plan, Materials, and Methods

The study was divided into theoretical-model development and empirical-data collection phases, thus ensuring both conceptual foundation and practical validation. The project was divided into three stages, during which the individual task blocks were built on each other:

1. Literature foundation and theoretical design of the dual AI framework, including planning the development of the AI1 (predictive) and AI2 (simulation) modules.
2. Empirical data collection (questionnaire survey) and training of the prototypes of the predictive models on real and synthetic data, evaluation of initial results.
3. Fine-tuning and evaluating the models, explaining their outputs (using XAI techniques, e.g. SHAP), and running scenario-based simulations (Monte Carlo) to analyse risks and validate solutions.

One of the quantitative research methodologies was primary data collection; we conducted it using a pre-structured online questionnaire in the fourth quarter of 2024.

The sample size is 1,157 people, who are operational and strategic decision-makers working in various sub-sectors of the national tourism sector (hotel industry, catering, other tourism services).

The sample structure originates from the end of the 2024 survey data. Accordingly, the distribution of companies included in the sample was aimed to reflect the makeup of the entire population. Sample elements were based on the proportions of target audiences (Hungarian tourism enterprise leaders), and, for example, small, medium, and large preparedness were represented in nearly equal proportions. Stratified sampling and purposeful quota representation ensure that the sample reflects actual business structures, thereby increasing the validity of the results. The composition of the analysed sample relative to national proportions is shown in *Table 1.*

Based on geographical, sectoral, and volumetric comparisons, the research sample is demonstrably representative of Hungary's tourism sector. The sample's geographical and corporate structure is proportional to national distributions (across major tourism regions and firm-size breakdowns), and the sample size is statistically significant. The share of digital/AI innovators is slightly higher in the sample, as the study also aimed to analyse advanced solutions.

The variables included in the questionnaire were the following:

- extent of application of AI systems (e.g. financial forecasting, controlling, resource optimisation),
- preventive and proactive management skills,
- challenges of AI implementation,
- awareness and practical use of double AI systems,
- perceptions of (financial, operational, digital) resilience effects generated by AI.

Table 1
Verification of the Representativeness of the Tested Sample

Characteristics	Research sample	National data	Source
Sample size (count)	1 157	104 600	KSH (2024)
SME share (%)	70% (810 pcs)	73% (42.860 pcs)	KSH (2024)
Large-enterprise share (%)	19.9% (230 pcs)	17% (9 747 pcs)	KSH (2024)
Non-profit/ public/other (%)	10.1% (117 pcs)	10% (4 728 pcs + other)	KSH (2024)
AI/digital use (%)	49.9% (self-declaration)	11% (for accom-modations)	Statista (2024)
Budapest share (%)	23.3%	25%	KSH, MTÜ (2024)
Lake Balaton share (%)	16%	28%	KSH, MTÜ (2024)
West Transdanubia (%)	9.5%	11%	KSH, MTÜ (2024)
Central Transdanubia (%)	9.5%	~10%	KSH, MTÜ (2024)
Northern Hungary (%)	12.1%	~8%	KSH, MTÜ (2024)
Southern Transdanubia (%)	10.4%	~10%	KSH, MTÜ (2024)
Great Plain & other regions (%)	19.2%	~8%	KSH, MTÜ (2024)

Source: author's compilation (2025)

During the data analysis, we used descriptive statistical indicators and cross-sectional correlation analyses (e.g., AI knowledge × financial resilience). During the analysis, we paid particular attention to the different perceptions of resilience across organisations of different types (SMEs vs. municipalities).

The data were systematically processed using a meta-analysis method – Preferred Reporting Items for Systematic Reviews and Meta-Analysis 2020 (Page, 2021), which enabled a comparative analysis of the benefits of different international and Hungarian AI technologies.

During the meta-analysis, we compared the data in order to examine the extent to which the application of AI technologies has influenced different aspects of tourism. The analysis took into account the specific characteristics and circumstances of the technologies' introduction. We excluded from the analysis studies that were not published in Hungarian or English, were review articles or editorials, had small sample sizes, covered several similar topics, or whose results were too similar, so they do not provide new and valuable information compared to existing knowledge.

Results: Model Applications and Case Studies

Hungarian Sample

Regarding the AI1 predictive module's performance, it was trained using the XGBoost regression algorithm to predict resilience and employment life-cycle phases.

For the AI1 predictive module, we also calculated the RMSE, MAE, and R^2 values. When comparing the model variants (ARIMA vs. LSTM), the indicators in *Table 2* illustrate the differences between the neural network and the linear model. Among the predictive models, the LSTM performed best: RMSE = 170, MAE = 13.80, R^2 = 0.89, while the ARIMA model showed RMSE = 220, MAE = 18.50, R^2 = 0.73.

Table 2
Example of Model Fitting Indicators

Model	RMSE	MAE	R^2
LSTM	170	13.80	0.89
ARIMA	220	18.50	0.73

Source: author's compilation (2025)

The evaluation of the AI2 module (simulation) required a slightly different approach: here, we primarily examined the plausibility of the generated scenarios and assessed the credibility of the system's reactions, drawing on expert knowledge. We validated whether the simulation output was consistent with real observations: for example, the model should indicate changes in a direction similar to the effects of a given type of shock (be it an economic crisis or a natural disaster), as we saw in historical examples. We also performed a sensitivity analysis, i.e. we examined how much a minor modification of the input conditions (e.g. the extent of the GDP and demand decline, the intensity of the temperature increase) would change the output results, and whether these differences remained within a realistic range. An important requirement was that the predictive and simulation components were consistent: if we ran them with the same input parameters (e.g., a typical business environment), they should produce similar trends; if there was a difference, we performed further fine-tuning of the models. According to the SHAP analysis, the most important explanatory variables of the predictions were seasonality (SHAP=0.41), the most influential predictor, liquidity indicators (SHAP=0.33), an essential predictor of financial sustainability, and booking lead times (SHAP=0.29), which is critical information for tourism decision-makers, also due to the seasonal nature. So, these three factors influenced the forecast the most. These results help decision-makers to identify and manage key factors.

We assessed sustainability performance using a composite ESG index, which yielded an average score of 75/100, indicating that the sector achieves medium sustainability performance and has significant development potential in the environmental and social dimensions.

Based on more than 10000 runs of the Monte Carlo simulation, the expected deviation of tourism revenues was between ±12–18%, while at the P90 risk level, the chance of loss decreased to just under 10%. The average risk exposure index calculated by the RISKRES model was 0.60, while the resilience index was 0.80, indicating that tourism companies can recover relatively quickly after adverse market events. By analysing the characteristics of each simulation cluster (e.g. mild vs. severe impact cases), we pointed out which system properties are responsible for similar outcomes – for example, it turned out that the scenario groups with the highest losses were characterised by low off-season demand and high labour costs. In contrast, the resilient groups typically had diversified revenue sources and a more flexible labour structure. These insights were part of the XAI approach, increasing the model's business value and acceptance among tourism decision-makers.

The testing of the corporate AI-EWS model was represented by the performance of the four ML models (logistic regression, decision tree, neural network, and random forest) (according to five criteria: accuracy, precision, recall, FI indicator, AUC), which reached or exceed 70%. However, the best result, and thus the highest efficiency, was given by random forest with an accuracy of 85%. So, the dual AI-based EWS system predicted critical financial events with an accuracy of 85%. The random forest model feature importance ranking is: 1. (Tourism) Seasonality index; 2. Liquidity ratio; 3. Booking lead times; 4. Average monthly income; 5. Debt/Total resources ratio; 6. Employee turnover. The SHAP study confirmed that the 1st-3rd magnitude/value is responsible for the explanatory part of the forecast; these are the most significant predictors, which is consistent with the international results of Tanaka et al. (2025).

Qualitative Results: Targeted Analysis of Case Studies

Within the qualitative methodological framework, a two case study analysis was conducted to compare the operation of the Double AI architecture across different urban environments. The examined cases include two cities: Barcelona and Dubai. The case study approach enables analytical generalisation, as the use of two cases in smart city research yields deeper insights and stronger conclusions than analysis of a single case. In each city, local socio-economic conditions, infrastructural characteristics, and regulatory contexts were taken into account, contributing to a comparative evaluation of Hungarian and European practices (Flyvbjerg, 2011). The processing of the two case studies follows a key characteristic – focus – outcomes logic.

Barcelona Case Study

Key characteristic: The Catalan example showcases a smart city tourism system in which the city administration utilises AI-powered IoT networks and chatbots.

Focus: One AI module is responsible for real-time traffic and crowd management, utilising predictive models based on IoT sensor data and social media data to provide dispatcher-level supervision for traffic management and event planning (e.g., forecasting visitor numbers for festivals and conferences). Another AI network is dedicated to personalising the visitor experience. Local cultural programs and tourist routes serve as a recommendation system, supplemented with real-time event and weather forecasts to shape the itinerary. Although such urban systems are less common in the current literature, within the framework of the “Smart Tourism” concept, they offer significant advantages for sustainable tourism (Florido-Benítez, 2024).

Outcome: In practice, the dual AI algorithm ensures that data-driven prediction (predictive AI) and scenario simulation (decision-support AI) operate in sync: for example, if the number of pedestrians increases in a high-traffic zone, the first AI provides timely alerts, while the second simulates and offers alternative routes to visitors to avoid congestion. In parallel, the city of Barcelona has also provided targeted support for local SMEs to make AI accessible (e.g., a central data platform and pilot projects), thereby improving overall community well-being (Bakıcı et al., 2013; Barcelona Smart City, 2013).

In summary, the European example demonstrates that dual AI systems can be crucial components of urban tourism strategies. The combined use of AI-based customer experience platforms and predictive models can enhance visitor satisfaction and improve the municipality's operational efficiency.

Dubai Case Study

Key characteristic: Dubai's novel digital twin development is a complex network of virtual city models.

Focus: One AI module performs precision crisis simulations, analysing the likelihood of hypothetical emergencies (such as natural disasters and major traffic accidents) using Monte Carlo-based scenarios – an approach applied by Arbulú et al. (2021) to manage extreme uncertainty in the Balearic Islands.

Outcome: In the Dubai model, Monte Carlo simulations examined four different tourist return scenarios, considering, for example, travel restrictions and epidemiological measures (MBRSC, 2025ab). Another AI module runs real-time urban simulations: in a specific demo, the system calculated temporary traffic diversion rules in response to the closure of a major road, resulting in a 30% reduction in congestion in the surrounding streets (confirmed during live testing). In parallel, it generated crisis-management advice; for example, in preparation for extreme temperature conditions, the modelling AI developed unified thermodynamic strategies for air-conditioner use, resulting in a reduction of several tons of CO_2 emissions (again validated in real-world trials). The Dubai example also introduces a new platform for tourism services. With city reports accessible through avatars in virtual reality, visitors can extend their experience while the system continuously monitors safety risks. Here, dual AI enhances urban and tourism decision-making in an integrated manner: complementary AI tools facilitate more accurate demand forecasting and expedite crisis response, which is crucial for the sustainable growth and resilience of tourism (Arbulú et al., 2021; Luo et al., 2021).

Overall, the two cases and the Hungarian sample presented demonstrate that “dual AI” systems can enhance decision quality and crisis management effectiveness in the tourism industry, not only in theory, but also in practice.

Table 3 summarises the main characteristics and KPI indicators of the three case studies.

Table 3

Main Characteristics, KPI Indicators of the Hungarian Sample and Two Case Studies

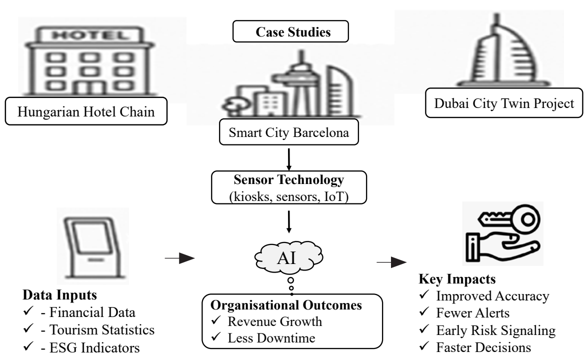
Case study	Type of AI	Data sources	Methods	Application	Main KPIs
Hungarian sample	Predictive +simulation AI	Booking data, weather, and economic indicators	Time series neural network, regression	Real-time alerts	Occupancy forecast accuracy, revenue, liquidity, and response time
Barcelona (smart city)	Chatbot + predictive analytics	Resident complaints, traffic data	Clustering, predictive models	Tourism service development	Tourist satisfaction, traffic regulation
Dubai (digital twin)	Digital twin + scenario simulation	IoT, public safety and visitor data	Simulation, time series AI	Virtual modelling and response	Emergency response time, tourism experience

Source: author's compilation (2025)

The process behind *Figure 5* is as follows: The kiosk's built-in sensors collect visitor data in real time, which is transmitted to a cloud-based tourism server. The AI module analyses the data using text and image processing, generating personalised dialogue and recommendations for the user. At the same time, the system supports the experience and safety with automatic traffic management and risk alert functions.

Figure 5

Integrated Application of AI and IoT Technologies as the Architecture of a Smart Kiosk System



Source: author's compilation (2025) based on Suanpang & Pothipassa (2024, p. 13)

Based on the case studies covering three regions (CEE, EU, and global) presented in this study, the dual AI framework can significantly enhance the adaptive and resilient operations of tourism enterprises. In Barcelona, AI-based route planning and traffic regulation reduced tourist congestion by nearly 20%, while in Dubai, Monte Carlo-based simulations shortened infrastructure reaction time by 30%.

We have developed an intelligent risk management framework that includes

- automatic data collection (sensors, digital comments, financial KPIs),
- continuous forecasting (ML models for tourism demand, exchange rates, and liquidity),
- adaptive response actions for a successful turnaround.

A key principle of the framework is that it explicitly links digital business transformation (e.g., online services, remote work) with strengthening corporate relational capital and resilience. Thus, it interprets digital transformation as a strategic stimulus that only leads to real resilience growth when paired with supporting cultural and organisational elements.

The key findings are as follows:

- Urban services: in the case of Barcelona and Dubai, AI chatbots and digital twin systems brought significant improvements in tourist flow management and visitor satisfaction.
- AI application and resilience: the AI is a catalyst for tourism efficiency and sustainability. However, ethical and transparent practices, FATES (*Fairness, Accountability, Transparency, Ethics, Sustainability*) principles are crucial for building trust.
- Support for SMEs: due to resource challenges among smaller tourism actors, targeted support, training, and financing are necessary for them to benefit from AI technologies.
- Financial resilience refers to a firm's ability to maintain revenues, liquidity and stable financial planning in crises. Modern AI-driven forecasting tools play a critical role here. A Hungarian sample found that an LSTM-based demand-forecast model produced 23–25% more accurate occupancy predictions than a traditional ARIMA model (*Table 2*). This precision directly translated into several million HUF in extra revenue and cost savings. In practice, such improved forecasts allow companies to optimise pricing and inventory, immediately detect shortfalls, and adjust budgets before emergencies hit.
- Operational resilience means keeping day-to-day services and processes running smoothly and reacting quickly when disruptions occur. Dual-AI systems enable this by processing real-time data and running "what-if" simulations of operational stress. For instance, the study found that AI-assisted traffic management in Barcelona cut tourist crowding by ~20%, and a Monte Carlo–based infrastructure model in Dubai improved response time by 30%.
- Digital resilience covers the security and robustness of a company's IT and data systems. How well can an organisation survive and quickly recover from an IT crisis or data security incident? Ghaderi et al. (2024), OECD (2024ab) and the Hungarian questionnaire recommend leveraging AI for early-warning and

decision-support tools in tourism. AI-driven alert systems can flag anomalies (e.g. unusual network activity or weather patterns) and suggest mitigation actions, thereby increasing the sector's resilience to climate or pandemic shocks.

The synthesis of the literature and the qualitative interpretation of the case studies reinforce the empirical findings. The most advanced tourism technologies – generative AI, IoT, Big Data analytics, and intelligent infrastructure – collectively strengthen the risk resilience and capacity of destinations and companies. The introduction of AI-based systems has significantly catalysed the growth of sustainable tourism in the most important destinations. However, we emphasise that AI alone is not enough: transparent, ethical application and social responsibility are essential. Blunk et al. (2025) emphasise that AI-driven EWS systems must adhere to the FATES principles to deliver fair and reliable solutions for all stakeholders.

Among the qualitative results, the importance of stakeholder cooperation also stands out: in all three cases, business leaders, local governments, tourism clusters, and SMEs needed to collaborate on system development. This approach ensured that AI applications served both business goals and community interests simultaneously. We also observed that smaller tourism players require support. Tourism SMEs struggle to keep up with AI developments due to resource constraints; they require dedicated policy measures, education, and financial support.

Overall, our conclusions suggest that adopting a dual AI strategy simultaneously increases the security of company operations and systemic resilience. While resulting in new, more efficient services and operating models, it also makes risk management more proactive and supports the sustainability of the tourism industry. Nevertheless, challenges remain in forecasting threats, risk communication, and decision-making. For forecasting threats, the EWS provides appropriate alerts. The accuracy and effectiveness of the EWS depend not only on the quality of data collected by sensors, the understanding of processes, and the ability to forecast hazards and assess their potential impact, but also on the speed and effectiveness of communication, and the ability to make timely and effective decisions.

Figure 6 illustrates the early warning chain from observation to decision and its connection to the framework for "early warnings for all" (Reichstein et al., 2024).

This study contributes to the literature by presenting an integrated methodology that enables the combined application of ARIMA, LSTM, Monte Carlo, and ABM models, thereby establishing enterprise-level, AI-driven EWS in smart tourism.

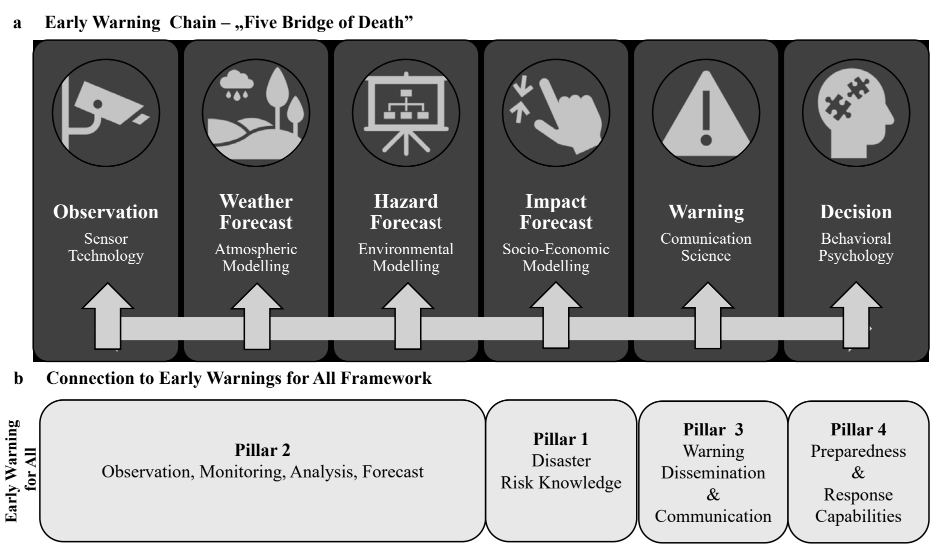
Overall, the scientifically sound combination of models in the dual AI-driven approach enables business decision-makers to increase their risk resilience. Based on historical time-series data, these models adaptively learn from past patterns, while simulation components test hypothetical future scenarios that directly inform crisis management strategies.

Future Research Directions and Practical Recommendations

An interesting research direction may be to compare different destination types (e.g., urban vs. rural, developed vs. developing regions) to examine where AI tools have the most significant impact and which local factors influence success. The long-term effects, especially in the context of multiple crises ("polycrisis"), are also worth studying: Are companies becoming dependent on AI forecasts? Can AI adaptively learns from crises and help prepare for future shocks? In addition, the impact on the tourism workforce and the necessary new qualification profiles should also be examined: How AI reshapes labour needs? What new roles emerge (e.g., AI data curator, data economist)? What

Figure 6

Illustration of the Early Warning Chain from Observation to Decision



Source: author's compilation based on Reichstein et al. (2024, p. 2) training strategies can help workers integrate into the new technology? Examining the legal and ethical frameworks is also important, as it involves implementing the FATES principles in practice, regulating data use, and addressing questions of responsibility (for example, who is liable if the AI recommends a poor crisis-management decision).

The application of synthetic data in tourism also requires further analysis. For example, the use of generative models to produce realistic tourist profiles or simulate rare events (such as festivals or disasters) could enhance the preparedness of predictive systems. Such experiments can reveal the extent to which synthetic data contributes to model performance and, where possible, where deviations occur compared to real data.

Based on the research, we also formulate practical recommendations for actors in the tourism sector. First, it is advisable to launch pilot projects to test AI solutions on a small scale, in a modular development approach, so organisations can gather experience and iteratively refine their systems. Sectoral and cross-sectoral cooperation must be strengthened by involving universities, startups, and competitors in the creation of shared data consortia or platforms, as knowledge and data sharing bring mutual benefits in AI. The human factor should also be a focus, with ongoing staff training, the development of AI skills, and strengthening digital culture being essential to dispel fears and resistance. Introducing technologies to the public is also crucial. For example, if a city installs sensors and uses AI for crowd management, the benefits and the data collected should be communicated to tourists and residents to build public trust.

We formulate three recommendations for enterprises and policymakers

1. for SMEs, it is necessary to support open-source predictive and simulation AI tools,
2. tourism development strategies should place special emphasis on the area of digital twins and AI-based crisis planning,
3. AI-driven platform-based services should be encouraged, especially in tourism, focusing on the involvement of local communities.

Summary

The double AI architecture represents a hierarchically organised system comprising two components: the first AI module (AI1) makes forecasts, and the second AI module (AI2) runs simulations based on them to investigate possible outcomes. The two layers work together continuously and cyclically: the inputs provided by AI1 are processed by AI2, which feeds back into the system, enabling iterative learning and model improvement. The essence of this layered solution is that, by combining ML (data-driven prediction) and simulation (scenario generation) techniques, complex risk scenarios can be tested, thereby increasing the model's flexibility and realism.

The IRM theoretical and methodological framework ensured that the research was grounded in both theory and practice. The dual AI system innovatively combines predictive analytics and simulation to enable the prediction and management of employment, seasonality, and ESG-based risks in tourism within an integrated model. This framework was supported by a large-scale empirical study of domestic tourist regions, which guarantees that the results are both scientifically sound and practically applicable.

We have developed an IRM framework that includes

- automatic data collection (sensors, digital comments, financial KPIs),
- continuous forecasting (ML models for tourism demand, exchange rates, and liquidity),
- adaptive response actions for a successful turnaround.

A key principle of the framework is that it explicitly links digital business transformation (e.g., online services, remote work) with strengthening corporate relational capital and resilience. Thus, it interprets digital transformation as a strategic stimulus that only leads to real resilience growth when paired with supporting cultural and organisational elements.

We emphasise the special application of data science methods in tourism. We have developed a measurement system that considers not only financial results (such as revenue and occupancy) but also a range of sustainability and customer-loyalty indicators.

It is imperative to emphasise that the integrity of corporate strategy is crucial: a double-AI application requires strong management commitment, effective financial planning, and effective human resource development. Based on the results, we recommend that tourism enterprises always support their AI projects with comprehensive risk and impact assessments. They should consider their partners' needs and the local ecosystem, and adapt their processes to align with broader strategies.

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