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Developing Early Warning Systems in the Era of Company Crisis Prevention

Judit Katalin Fejes[1]; Etelka Éva Katits[2]

[1] University of Pannonia, Zalaegerszeg University Center, Department of Finance and Management, Zalaegerszeg, Hungary

[2] University of Pannonia, Zalaegerszeg University Center, Department of Finance and Management, Zalaegerszeg, Hungary

Corresponding Author Email: fejes.judit@zek.uni-pannon.hu

Abstract— This study explores the application of artificial intelligence (AI) in corporate crisis prevention, with a particular focus on the digital transformation and development of Early Warning Systems (EWS). Four major thematic areas are identified for further elaboration: (1) Double and Triple AI Models: the collaboration of multiple AI systems to generate synthetic data and scenarios for crisis recognition or prevention; (2) The Role of Edge AI: real-time financial forecasting and monitoring through local data processing for immediate alerts; (3) AI-Based Crisis Prevention Frameworks and Sustainable Corporate Governance: integrating AI into improving ESG (Environmental, Social, and Governance) performance and enabling more transparent decision-making; (4) SME-Friendly AI Solutions: EWS developments within the framework of digital transformation that apply to **S**mall and **M**edium-sized **E**nterprises. The research employs a mixed-methods approach: a review of the literature, analysis of international and Hungarian case studies, and the development of an adaptable hypothetical model for the Hungarian corporate environment. The findings demonstrate that AI-supported EWS can identify corporate risks with significantly greater accuracy and consistency compared to traditional systems. However, human expertise remains crucial for the continuous learning of the models and the appropriate handling of alerts. The study offers recommendations for companies – especially SMEs – on the implementation of AI-driven early warning mechanisms, emphasising the importance of change management, regulatory compliance, and human oversight to ensure that the adoption of AI-based EWS results in sustainable and crisis-resilient operations. Finally, it presents the concept of a pilot model intended for application in Hungary, integrating the above innovative approaches and aligning with Hungary's digital transformation and AI strategies.

Keywords: artificial intelligence, crisis prevention, digital transformation, early warning system, sustainable corporate governance.

1. Introduction

In a globalised and digitised economic environment, companies must adapt to unprecedented rates of change and emerging risks. Corporate crises – whether financial difficulties, market downturns, or reputational disruptions – require early detection and prevention to ensure the long-term survival of organisations. The purpose of **E**arly Warning **S**ystems (EWS) is to forecast potential crisis situations, allowing management to intervene proactively. Traditional EWS are mostly based on financial indicators and static models (e.g., financial ratios such as the Altman Z-score), but these are often limited in flexibility and reactive in nature. According to the literature, existing corporate risk signalling systems face several weaknesses: they often rely on a single model or dataset, struggle to adapt to rapidly changing market environments, and depend heavily on historical data. As a result, companies may miss the opportunity for timely intervention due to delayed or inaccurate warnings (Fang, 2025). The 2008 financial crisis and the COVID-19 pandemic have both emphasised the need for new approaches to predict and manage unexpected shocks.

The emergence of **A**rtificial **I**ntelligence (AI) and machine learning offers fundamentally new opportunities in the development of EWS. Recently, researchers and professionals have increasingly focused on integrating advanced data analytics methods and AI algorithms into risk management (Fang, 2025; Machado et al., 2025). By using big data and machine learning, financial distress forecasting can be significantly improved compared to traditional models (Edwards et al., 2025; Machado et al., 2025). For example, a recent study analysing data from Chinese companies found that the adoption of corporate AI technologies can in itself serve as an early warning signal—financial difficulties are more accurately predicted in companies using AI because their innovativeness and data-conscious operations serve as complementary risk indicators alongside traditional metrics. This suggests that AI-based indicators provide stable, complementary information that creditors and regulators can also use in risk assessment (Meng et al., 2025).

This study explores the key areas and practical aspects of the AI-based EWS concept. **Figure 1** outlines the central elements of the analysis, which are as follows:

(1) Implementation of double and triple AI models: This is an innovative approach where multiple AI models collaborate to forecast risks. The "double AI" model refers to the integration of two distinct AI systems (e.g., a generative and a predictive algorithm), while the "triple AI" model involves the synergy of three AI modules. These systems can generate synthetic data and scenarios—such as potential crises—which another AI module evaluates to estimate expected impacts. This approach aims to supplement traditional models that rely solely on historical data and draw attention to extreme but possible future events (Matthew, 2025).

(2) Edge AI for real-time risk signalling: The integration of edge computing and AI enables local, real-time data processing, rather than traditional cloud-based solutions. The financial sector and corporate governance, where millisecond decisions are often necessary for stock trading and liquidity management, find this particularly significant. Real-time monitoring and alerts "at the data source" (e.g., bank branches, sensors, or branch servers) allow immediate signalling of hazardous trends without first sending the information to a central server. This not only reduces latency but also addresses bandwidth and data privacy concerns, as sensitive data need not be continuously transmitted externally (Deekshith, 2025).

(3) AI integration into sustainable corporate governance: AI can drive breakthroughs not only in financial metrics but also in enhancing companies' **E**nvironmental, **S**ocial, and **G**overnance (ESG) performance. As part of sustainable corporate governance, AI-based analyses can help management gain a more comprehensive view of risks and opportunities, including environmental risks (e.g., emissions, climate change impact), social impacts (e.g., customer and employee satisfaction, ethical risks in supply chains), and governance compliance (e.g., violations, financial anomalies). Research shows that the use of AI improves companies' information governance: it increases transparency, facilitates internal information sharing, and reduces information asymmetry – leading overall to better ESG performance. For example, a comprehensive analysis among large Chinese companies revealed that AI implementation significantly improved their ESG indicators – especially the quality of environmental reports, supply chain management, and reduced agency costs (Zhou et al., 2025). Similarly, another study pointed out that applying AI technologies contributes to sustainable corporate development, with ESG acting as a mediating factor between AI adoption and improved sustainability performance (Xiao & Xiao, 2025). This indicates that AI indirectly strengthens corporate resilience and fosters long-term value creation by enhancing ESG practices.

(4) SME-friendly AI solutions in crisis prevention: SMEs form the backbone of national economies, yet their financial sustainability is often vulnerable due to limited resources and market fluctuations (Edwards et al., 2025). For them, cost-effective, easily applicable EWS solutions aligned with digital transformation tools are especially important. Recent studies confirm that AI-driven early warning models can significantly improve the accuracy of financial distress forecasting for SMEs, providing timely alerts to allow for intervention (Edwards et al., 2025). According to Gu et al. (2025), the challenge for SMEs lies in ensuring sufficient data volume and quality, which is why more focus is being placed on innovative methods such as generating synthetic data for rare events (e.g., modelling bankruptcies or insolvencies) and leveraging cloud-based services and platforms that make AI-based analytics available to smaller companies in the form of "EWS as a service". Additionally, the human factor and competency development are crucial: SMEs need to equip their employees with digital and AI skills. An IA government programme has been launched to provide digital and AI training for SME employees, recognising the importance of digitisation and AI expansion in improving competitiveness (Bráder, 2025).

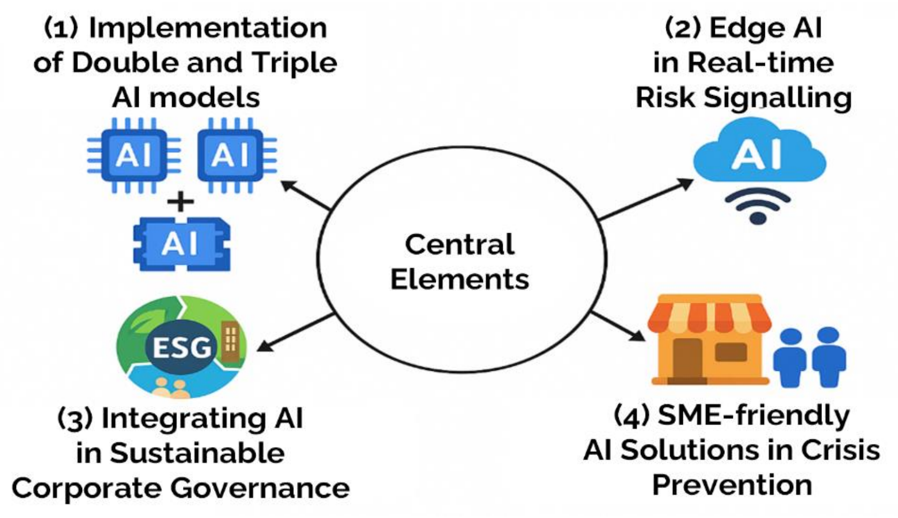

Figure 1. The Central Elements of the Study
Source: Author's compilation

Due to the novelty of the four focus areas mentioned above, there is a lack of comprehensive databases and empirical studies on the topic. This publication aims to address this gap through a framework-based analysis that examines these aspects in a unified manner. The objective of the study is to formulate and answer the following key research questions (RQ):

RQ1: How can double and triple AI models contribute to the early prediction of corporate crises? – This includes investigating how the cooperation of multiple AI systems (e.g., combining generative and predictive AI) can produce synthetic data and "what-if" scenarios, and how these improve the estimation of crisis probabilities.

RQ2: What role do Edge AI technologies play in real-time financial monitoring and alerting? – Specifically, we seek to understand to what extent local data processing (Edge computing) increases the speed and reliability of early warnings, for example, in financial services or data-intensive industries.

RQ3: How can AI-based early warning mechanisms be integrated into sustainable corporate governance frameworks, and how can these solutions be made accessible to SMEs during digital transformation? – This question has a double focus: on one hand, it explores how AI can support governance quality and ESG goal achievement (e.g., transparency, risk ethics, compliance improvement); on the other hand, it examines under what conditions smaller-resource companies can adopt these advanced EWS technologies.

The structure of the study is as follows: Chapter 2 reviews the relevant domestic and international literature, presenting the evolution of EWS and the rise of AI in this field. Chapter 3 outlines the applied research methodology, including literature analysis and case study methods. Chapter 4 presents the findings in four subsections, covering the application of double/triple AI models, Edge AI applications, AI-based integration into corporate governance (ESG), and SME-focused solutions, supported by case studies and practical examples. Chapter 5 outlines a hypothetical model for application in Hungary, introducing the key elements of a potential pilot project. Finally, Chapter 6 summarises the conclusions, outlines future research directions, and offers practical recommendations for policymakers and corporate leaders.

2. Literature and Historical Review

2.1 The Evolution and Challenges of EWS

The concept of corporate EWS is not new: models aimed at forecasting financial health have existed since the 1960s, with the most well-known example being Altman's Z-score, which estimates bankruptcy probability based on a few accounting ratios. Traditional systems are typically retrospective in nature, relying on trends in historical data. While these models can be useful for a certain degree of forecasting, they have several limitations. They lack dynamism and a multidimensional perspective, typically focusing solely on financial indicators while ignoring market, macroeconomic, or behavioural factors (such as management decisions or strategic changes). As noted in Chapter 1, many traditional EWS rely on a single model or data source, making them inflexible in the face of unexpected situations. For example, a system based solely on balance sheet data may fail to signal an impending crisis caused by market losses as its predictive variables "look backwards". Moreover, heavy dependence on historical data may result in a system that only detects crises similar to past ones and fails to recognise structurally new types of risks (Fang, 2025).

By the early 21st century, globalisation and technological advancement introduced new types of risks (e.g., complex financial derivatives, breakdowns in global supply chains, and social media-driven reputational crises) that traditional EWS struggled to handle. These shortcomings have created a demand for more advanced, data-driven solutions. Recent literature increasingly demonstrates how modern data analysis techniques can be integrated into risk forecasting. Fang (2025) points out that most earlier systems are unable to respond in real time to constantly changing market conditions and are not effective in handling complex or uncertain information. As a result, researchers have begun developing new models that combine various methodologies (e.g., integrating statistical and AI-based approaches) to enhance accuracy and speed.

So-called hybrid models and ensemble techniques have emerged in risk forecasting. Their key characteristic is combining multiple algorithms or models within a single framework, leveraging the strengths of each. In his study, Fang (2025) combines fuzzy C-means (FCM) clustering with the Random Forest (RF) machine learning model to improve the forecasting of corporate operational risks. FCM serves as a preprocessing step by segmenting companies based on similar features, while RF performs refined forecasting on these clusters. This multi-stage model was significantly more accurate and responsive than traditional single-stage approaches, with substantial improvement in alert accuracy and reduction in false alarms. The author emphasises that such integrated methods enhance system adaptability across different industries and situations and help handle multidimensional data better.

Overall, a paradigm shift is increasingly evident in the development of EWS: from static, deterministic models toward dynamic, learning-based systems. The new EWS models rely on real-time data streams, machine learning, and a broad variable set to provide a more comprehensive picture of corporate risks. This lays the foundation for the specific innovations discussed in the following subsections, such as double/triple AI, edge computing, or the integration of AI into corporate governance. Below, we provide a detailed overview of these concepts and the relevant literature associated with them.

2.2 The Application of AI in Financial Distress Prediction

AI and machine learning have already proven effective across a wide range of fields, and financial risk forecasting is no exception. AI is particularly well-suited to processing large volumes of financial data – such as balance sheets, income statements, cash flows, and market prices – and identifying patterns within them. Numerous studies have demonstrated that AI-based models outperform traditional statistical models in predicting corporate financial distress and bankruptcy. Malakauskas & Lakštutienė (2021), for example, compared logistic regression, neural networks, and the random forest algorithm for solvency forecasting based on a European sample of 12,000 SMEs. Their results showed that random forest was the most effective, especially when panel datasets and the firm's credit history over multiple periods were taken into account (Edwards et al., 2025). The best model was able to predict 12.7% more negative outcomes (e.g., loan defaults), and early warning signals allowed the bank to avoid losses in 67.6% of such cases (Machado et al., 2025)—a substantial improvement over trigger-based systems relying on traditional indicators.

The advantage of using AI lies not only in improved accuracy but also in the ability to incorporate new types of data. In today's digital age, companies generate massive amounts of unstructured data: news articles, social media posts, customer reviews, search trends, etc. Machine learning – particularly natural language processing (NLP) and big data analytics – Is capable of leveraging this information. For instance, Myšková & Hájek (2020) analysed the text of corporate annual reports and found that the "risk tone" present in these documents (i.e., the language and emotional tone used by management) had an impact on future financial performance (Zeng, 2022). A machine learning model that monitors the sentiment or risk signals embedded in textual reports may detect warning signs earlier than models relying solely on numerical financial indicators. Similarly, Liu et al. (2022) showed that incorporating alternative data – such as online search volumes or news frequency – enhances the effectiveness of distress forecasting.

Machine learning also enables models to learn and adapt over time. Traditional static models typically use fixed parameters, while most ML algorithms – particularly neural networks and boosting techniques – can be continuously refined as new data becomes available. This is a critical advantage in today's volatile environment, as models are able to "follow trends." However, it should be noted that machine learning is not a miracle solution: without appropriate variables and quality data, it cannot produce reliable forecasts. Therefore, in the development of corporate EWS, it is essential to carefully select relevant financial and non-financial variables, ensure input data quality, and maintain model interpretability. The latter – transparency – is especially important in the financial sector and corporate governance, where decision-makers must be able to understand why a model is signalling a crisis. To support this need, an increasing number of studies focus on tools for Explainable AI (XAI), such as applying SHAP (Shapley Additive Explanations) values in financial models (Machado et al., 2025).

In summary, integrating AI into financial distress prediction systems offers several advantages: it improves prediction accuracy, enables the inclusion of new data types (e.g., textual and streaming data), and makes the models adaptive. This lays the groundwork for the first major focus area of our study – double and triple AI models – which essentially represent the further extension of the AI toolkit through the generation of crisis scenarios and system-level predictive modelling.

2.3 Double and Triple AI Models: Generative and Collaborative AI Systems

The terms "double AI" and "triple AI" refer to architectures in which two or three AI components operate in a coordinated manner to solve a complex task. These concepts are still considered novel in the literature and currently lack standardised definitions. In this study, we use them as terminology introduced by the authors. A double AI model typically consists of a pairing between a generative AI (which creates new data or scenarios) and a discriminative or predictive AI (which performs classification or regression). The triple AI model adds a third component to this setup, which may be an optimising/controller AI – such as a reinforcement learning agent that iteratively refines the generated scenarios or reviews predictions – or another separate model that represents a different methodological approach.

2.3.1 The Role of Generative Models in EWS

One of the major developments in AI in recent years has been the rise of generative models. These are algorithms (such as Generative Adversarial Networks – GANs, or Variational Autoencoders – VAEs) capable of producing realistic new data samples after learning the distribution of existing data. Generative models offer tremendous potential in EWS, as they make it possible to simulate "rare events" that are underrepresented in historical datasets. In financial supervision and risk management, experiments are already underway to enhance models with synthetic data generation for better handling of extreme events (Gu et al., 2025). For example, Jiang et al. (2024) generated synthetic data on rare event classes – such as fraud, market manipulation, and sudden crashes – for financial regulators, in order to balance the training datasets of supervisory models. Their results showed that including generated data improved the performance of the risk detection framework and provided more informative data for monitoring, allowing financial supervisors to detect anomalies earlier (Gu et al., 2025). In practice, this means that by training on databases enriched with AI-generated "synthetic" fraud cases, supervisory models became more sensitive to real indicators of fraud, enabling early warnings to be issued before traditional systems would react.

Another application of generative models is in scenario analysis and stress testing. Traditionally, financial stress tests are based on a limited number of manually designed scenarios (e.g., "X% GDP decline, Y% interest rate increase"). In contrast, generative AI can automatically and data-drivenly generate a wide range of possible crisis scenarios, accounting for nonlinear relationships among variables. For example, in a study on energy market resilience, GAN and VAE models were used to generate high-fidelity, diversified crisis scenarios – such as the impact of geopolitical blockades, cyberattacks, or extreme weather events on the energy system. The generated scenarios were novel yet realistic, reflecting the characteristics of historical crises while also combining them in new ways (Edwards et al., 2025). This enabled decision-makers to prepare for a broader spectrum of risks, going beyond the traditional "worst-case" scenario thinking. Thus, generative models augment human strategic foresight by providing quantified "what-if" analyses to support crisis planning.

2.3.2 Collaborative AI Models and Multi-Agent Systems

The other component of double/triple AI systems is typically a predictive model that evaluates the output of the generative module. For example, in a double AI EWS, synthetic financial indicator sequences or macroeconomic trajectories generated by a GAN are evaluated by a second AI model (e.g., a deep neural network) to determine whether corporate bankruptcy would occur under that trajectory. This allows us not only to answer questions like "what happens if GDP drops by 5%?" but also to explore many possible combinations generated by the generative model, while the predictive model flags those combinations that are dangerous for the company. In essence, this enables the mapping of a firm's stress tolerance – identifying which variables, and to what extent of deterioration, lead to a crisis. Although still largely in the experimental stage, this approach can significantly enhance the information content of early warnings: instead of simply outputting a model score indicating increased bankruptcy risk, it allows for the association of specific scenarios with risk levels.

In triple AI models, a third agent often appears, coordinating or optimising the interaction between the other two. This third agent might be a reinforcement learning component that, through continuous feedback, improves the generative model's scenarios to focus on the most relevant or "most informative" cases. In the previously mentioned energy market resilience framework, the authors also integrated an agent-based simulation model: the generated crisis scenarios were run in an agent-based environment simulating the interactions of different actors (e.g., regulators, energy providers, consumers), and reinforcement learning was used to model adaptive responses (Edwards et al., 2025). As a result, the system not only indicated that a given event was dangerous but also predicted how actors would respond and what secondary effects might emerge (e.g., domino effects, contagion). This type of multi-agent collaboration creates a holistic simulation: the generative module provides the input, the predictive module evaluates it, and the third module optimises or connects the system to a broader model.

Naturally, the development of double/triple AI models comes with several challenges. One such challenge is computational complexity: running and integrating multiple AI systems in parallel can demand significant data and resources. Additionally, validating the quality of the generative models is critical –it must be ensured that generated scenarios are economically realistic. As one expert put it, synthetic scenarios must be economically coherent because unrealistic assumptions can mislead risk assessments (Nexastack, 2025). To ensure this, a common method is to train generative models with domain-specific constraints or expert rules, and to subject the results to expert validation.

In summary, double and triple AI models represent a promising direction for the future of corporate EWS. Although few practical implementations have been reported so far, research findings are encouraging: systems enhanced with synthetic data and composed of multiple models are better at identifying rare but critical risks and respond more rapidly to changes than traditional single-model counterparts (Matthew, 2025). In Chapter 4.1, we will present concrete examples of the application and results of such models in crisis prevention.

2.4 Edge AI: Edge Computing-Based AI for Real-Time Forecasting

Edge computing refers to processing data as close as possible to where it is generated or used. This paradigm was originally designed to reduce network latency (e.g., through content delivery networks – CDNs), but today, AI has also reached the edge environment. Edge AI means that AI algorithms (e.g., neural networks) – or at least the inference (prediction) part – are executed at the network's edge, on local devices, rather than in a central cloud (Deekshith, 2025).

In the context of financial and corporate risk management, the use of Edge AI is particularly relevant for improving real-time responsiveness and reliability. There are numerous situations where every millisecond counts—typically in capital market trading (e.g., high-frequency trading – HFT), or even in a bank's cybersecurity systems (e.g., detecting fraud at the moment of transaction). Edge AI allows the decision-making algorithm to run directly where the data is generated, enabling virtually immediate responses. For instance, a credit card fraud detection AI can run on the branch server of a bank or within a regional payment processing centre, eliminating the need to wait for the data to reach a remote data centre. According to Mastercard, deploying advanced machine learning models to the network edge – directly to card readers and payment gateways – has helped prevent billions of dollars in fraudulent transactions annually, as the system filters out suspicious patterns in real time, before the transaction is completed. This is a practical example of Edge AI delivering early warnings in the truest sense: in real time, at the point of transaction.

Another major benefit of Edge AI in the financial sector, beyond reducing latency, is bandwidth savings and data sovereignty. For many banks and corporations, it is essential not to move customer data outside their premises (e.g., to the cloud), partly due to data protection regulations (e.g., GDPR), and partly because local data processing is often mandated by regulators. Edge AI supports this: data remains on-site, and only the necessary results or aggregated indicators are transmitted. For multinational banks, this means AI models running on edge servers in local branches can comply with data residency requirements, helping meet GDPR and other regulatory obligations. From a security perspective, the picture is mixed: on one hand, keeping data locally reduces the likelihood of large-scale data centre cyberattacks; on the other hand, many small edge devices can present a wider attack surface topic we will explore at the end of Subchapter 2.4 under challenges.

In the context of corporate crisis prevention, Edge AI can bring a breakthrough, particularly in real-time monitoring. Imagine a large international company with multiple sites and production units. A traditional EWS may rely on monthly financial reports or quarterly indicators – whereas in a factory equipped with IoT sensors, Edge AI collects and analyses data every second (such as machine temperature, energy consumption, production speed, etc.) and immediately alerts if it detects an unusual pattern. Suppose a critical machine's vibration sensor detects abnormal movement: an AI running on an edge device recognises that this pattern resembles a signal preceding a past malfunction and instantly sends an alert to the maintenance team. This enables the machine to be repaired before it causes production downtime – thereby preventing a potential operational crisis.

The same principle can be applied to financial data as well: with mobile edge computing, a company's local branch systems can forecast liquidity problems or detect anomalies in cash flow. Zeng (2022) found that financial management supported by mobile edge computing responds more quickly to changes in cash movements, and by using pre-loading techniques (which estimate the next data requirement at a given site), it is possible to reduce reporting delays in financial risk alerts by 2–5%. While this percentage may seem small at first glance, in critical situations – such as a sudden liquidity crisis – a faster reaction can be life-saving.

We must also highlight specific financial use cases of Edge AI. **Table 1** summarises some key areas where Edge AI has already been implemented or is emerging in the sector:

Banking applications: Banks use Edge AI to personalise customer service, enhance security and fraud prevention, and improve operational efficiency. For example, HSBC has introduced the Pepper robot in some branches – an AI-powered humanoid capable of handling basic customer enquiries on-site in real time using natural language processing. Pepper is connected to edge servers that process speech recognition and emotion detection, allowing it to respond immediately to customers, improving both the customer experience and reducing the burden on staff. Another example is the previously mentioned fraud detection: banks run transaction-analysis AI on edge devices installed in branches or payment gateways, enabling them to block suspicious transactions in real time at the local level (Deekshith, 2025).

Investment management and stock trading: Here, reducing latency provides a direct competitive advantage. A typical example of edge computing is that trading firms co-locate their servers near stock exchange data centres (i.e., placing them on the "edge") to minimise the delay from the last few kilometres. Alongside this, the AI model also runs locally—for instance, an arbitrage trader uses Edge AI to monitor multiple markets simultaneously, and when it detects a pricing anomaly (e.g., the same stock trading at different prices on two exchanges), it acts instantly. Such a system can only function efficiently if the model is deployed right next to the data source; otherwise, network latency would cause it to miss the lightning-fast market opportunity (Deekshith, 2025).

Insurance and risk forecasting: The combination of IoT and Edge AI is already bringing transformative change to risk management in the insurance industry. Smart home sensors (e.g., smoke and water leak detectors) continuously monitor properties. These devices use local AI to evaluate incoming signals and, upon detecting something unusual (like a water leak), immediately alert and intervene (e.g., automatically shut off the water). This enables insurers to prevent significant damage events, as early warnings and interventions can minimise the impact of a pipe burst. Similarly, in auto insurance, onboard AI algorithms analyse driving behaviour in real time (acceleration, braking, cornering dynamics), creating a live risk profile of the driver (Deekshith, 2025). Based on this, insurers can dynamically adjust premiums (usage-based insurance) or send alerts to the driver in case of dangerous manoeuvres.

Area	Application	Advantages	Example/Research
Banking Applications	Customer service (e.g. Pepper robot, NLP, emotion recognition)	Real-time customer experience	HSBC: Pepper robot
	Security and fraud prevention (local transaction analysis)	Instant blocking of suspicious transactions; Employee relief	Edge-based fraud detection (Deekshith, 2025)
Investment Management and Stock Trading	Local AI models near exchanges	Minimal latency	Edge server colocation; Arbitrage trading (Deekshith, 2025)
	Real-time detection of exchange rate anomalies	Immediate reaction to market opportunities; Competitive advantage in fast trading	
Insurance and Risk Forecasting	Smart sensors (water, smoke, home insurance)	Early alarm and intervention	IoT + Edge AI combination
	In-car AI for real-time driving profile	Dynamic pricing (usage-based insurance); Damage minimization	Real-time driver profile (Deekshith, 2025)
Research Results	XGBoost models in financial stress	97% accuracy	Ionescu et al. (2025)
		Edge performance indicators (latency, CPU utilisation) as “early warning” signals	
Challenges	Regulatory compliance, auditing	Complex models simplification required	Deekshith (2025)
	Infrastructure costs	Management of hundreds of edge points	
	Computational constraints (model compression) Security risks	Every device is a potential attack surface	

Table 1. Some Key Areas Where Edge AI Has Already Been Implemented
Source: Author’s compilation based on Deekshith, 2025; Ionescu et al, 2025

Research and industry reports strongly support the benefits of Edge AI. In a synthetic experimental environment, Ionescu et al. (2025) showed that reducing system latency and efficiently utilising local resources significantly improves decision quality during financial stress scenarios. Their XGBoost models achieved 97% accuracy, and the study concluded that performance metrics for edge infrastructure (such as network latency and local CPU usage) can serve as early indicators of systemic vulnerability – and should be integrated into financial EWS. The finding is an exciting insight: it suggests that if, for example, the edge network in a trading system becomes saturated and slows down, that itself can act as an “early warning” that the system is under stress. Since the 2010 “flash crash”, we've known that capacity issues in technological infrastructure can themselves trigger market crises.

Naturally, Edge AI also has challenges and limitations that must be addressed for completeness. One such issue is **regulatory and compliance requirements**: AI models must be validated and audited at each edge point, which can be difficult if they’re deployed across hundreds of ATMs or branch servers. Regulators may require that every decision made at the edge is traceable and explainable (e.g., why a transaction was instantly rejected by the system). This demand necessitates resource-intensive logging and centralised oversight. Another challenge is **infrastructure cost**: deploying and maintaining many edge nodes can be expensive, and if poorly planned, costs may outweigh the benefits. Additionally, **computational limitations** are key: edge devices typically have less processing power than a cloud data centre, so AI models must be optimised (e.g., via model compression, quantisation) for local execution (Deekshith, 2025). These issues may require trade-offs in model complexity – very complex deep learning models might not run at the edge, necessitating the use of simpler alternatives.

Finally, there’s the matter of **security**: while local data handling is advantageous for privacy, every edge device is a potential attack surface. Strong encryption, tamper-resistant hardware, and secure communication are essential – otherwise, decentralisation could lead to system vulnerability (Deekshith, 2025).

In summary, Edge AI in corporate EWS offers the promise of making decisions at the right place and the right time. By pushing critical analytics to the edge of the network, it reduces reaction times and increases availability – especially vital in emergencies or rapidly evolving crises. In the next chapters, we will see how this approach can be combined with previously discussed AI models and what concrete results can be achieved in practice.

2.5 AI in Sustainable Corporate Governance and ESG Performance

The quality of corporate governance and the commitment to sustainability principles (ESG: Environmental, Social, Governance) are now closely intertwined with corporate risk management. Numerous corporate crises (e.g., accounting scandals, environmental pollution incidents, labour conflicts) have highlighted that early signs of risks often emerge in governance and sustainability areas. Therefore, when developing modern EWS, it is crucial to consider that AI can support not only financial figures but also corporate governance processes and ESG indicators.

The application of AI in corporate governance occurs on multiple levels. On the one hand, as discussed above, it enhances transparency: machine learning can collect large volumes of corporate information (reports, records, market data) and uncover patterns that might escape the attention of human leaders. Zhou et al. (2025), in a quasi-natural experiment, examined the impact of AI on the ESG performance of Chinese publicly listed companies and found that AI significantly improved ESG indicators, particularly through advancements in corporate information management (better internal information sharing, reduced information asymmetry). According to Zhou et al. (2025), specific outcomes of this more advanced information culture included more accurate reporting of environmental data, responsible procurement and supply chain management (as AI helped optimise and monitor supplier networks), and a reduction in agency problems (e.g., managers found it more difficult to hide issues from owners). This suggests that AI can strengthen corporate governance controls: for instance, an AI-based system could automatically verify adherence to budgetary discipline or compare management forecasts with actual figures and flag excessive deviations (which could indicate manipulation).

On the other hand, AI can assist in regulatory compliance and risk-ethics management. Large corporations must comply with a multitude of regulations (financial rules, data protection laws, environmental standards, etc.). Replacing traditional compliance functions, AI can monitor corporate activities in real time and provide early warnings if a regulatory breach is suspected. For example, banks use AI in anti-money laundering efforts: algorithms continuously monitor transactions and customer data, alerting compliance departments when typical money laundering patterns are detected (e.g., unusually large round-number transfers, movement of funds between corporate structures). These systems go beyond traditional rule-based monitoring by using self-learning capabilities to detect new tricks, thus becoming more effective in enforcing compliance.

Regarding the environmental (E) and social (S) dimensions of sustainability, AI can also be deployed in multiple ways. Environmental monitoring: with the help of sensors and AI, companies can monitor their environmental emissions in real time (e.g., a factory's gas emissions or water pollution) and intervene immediately if a threshold is exceeded (Xiao & Xiao, 2025). AI can also contribute to improving energy efficiency – for example, by predicting energy needs and optimising machine operations, thereby reducing environmental impact. Social responsibility: AI can be applied in HR (e.g., assessing employee satisfaction by analysing internal emails/messages, forecasting turnover) or in processing consumer feedback (e.g., sentiment analysis from social media or customer service chats to detect whether there is a growing wave of complaints about a product). All of these can serve as early warning signs of emerging issues – for instance, if employee sentiment deteriorates on internal forums, AI can alert management, helping to prevent a labour crisis or strike.

In relation to corporate governance and sustainability considerations, new concepts such as "Augmented Analytics" and "Augmented AI" have emerged, emphasising the collaboration between human decision-makers and AI systems. Under the acronym **AAAI-EWS**, we refer to an augmented, AI-driven early warning system that integrates everything discussed so far: the synergy of multiple AI models, real-time edge analytics, and alignment with corporate governance processes. In practice, this complex system would be designed to signal any kind of corporate crisis – whether financial, operational, or reputational—at the earliest possible stage.

Based on the literature review in this subsection, it can be stated that AI has a positive effect on companies' sustainability performance and improves the transparency and manageability of risks. The study by Xiao & Xiao (2025), based on a survey among managers, concluded that the application of AI technologies brings benefits in three areas: corporate governance (better decision support, risk monitoring), environmental management (real-time measurement and response, emissions reduction), and social responsibility (data-driven insights into social impacts). According to the research, ESG acts as a mediator between AI and corporate performance – that is, in cases where AI was more deeply integrated, improvements in ESG led to better sustainable development indicators (Xiao & Xiao, 2025). This reinforces the need to perceive EWS not merely as financial alert mechanisms but as complex corporate governance tools that also support the achievement of sustainability goals.

2.6 SMEs on the Threshold of Digital Transformation: Crisis Prevention in the Small Business Environment

For SMEs, the application of EWS is particularly important, as these companies are typically more vulnerable to shocks, with fewer reserves and limited expert capacity to handle crises. At the same time, SMEs are key players in the economy, with significant weight in both employment and GDP contribution. Therefore, preventing crises in SMEs is not only an individual but also a national economic interest.

The literature shows that predicting financial distress in SMEs poses a unique challenge, as publicly available data is limited and non-standard operations are common (e.g., informal financing in family businesses). Edwards et al. (2025) therefore proposed a hybrid AI framework specifically for monitoring the financial health of SMEs. In their research, they combined supervised learning (classification models trained on classical financial indicators) and unsupervised learning methods (clustering, outlier detection) to extract as much insight as possible from heterogeneous SME data. In addition, they placed emphasis on model interpretability, since SME managers are typically not data analysts and may not understand or accept alerts from a “black box” AI model. The results showed that advanced AI models (e.g., gradient boosting machines, neural networks) outperform traditional statistical methods in predicting SME bankruptcies – especially when proper feature engineering and variable selection precede model building (Edwards et al., 2025). The study highlighted that an integrated data perspective is key even for SMEs: it's not enough to look at balance sheet data alone; one must consider the company's operational environment (sector trends, macroeconomic conditions) and even "soft" information (owner’s reputation, customer reviews, etc.).

In practice, several initiatives aim to support SMEs with early warnings. The Early Warning Europe project (implemented in cooperation among several EU countries), for instance, established a network of advisors who assist SMEs facing crisis risks—before the situation becomes irreversible. While AI was not the central focus in this project, experiments were carried out in the background to develop AI-based bankruptcy risk models, helping advisors identify the most at-risk businesses for intervention.

Digital transformation is inevitable for SMEs, and this also presents an opportunity to introduce modern EWS solutions. Many SMEs already use cloud-based accounting or ERP systems (e.g., online invoicing software), which generate vast amounts of data. These systems can incorporate AI-based modules that monitor business finances and alert the owner if, for instance, a deteriorating trend in liquidity or revenues is detected. A hypothetical example: an invoicing system used by a small retail company detects via AI that in the past two months, revenue has dropped by 20% compared to the same period last year, and this is coupled with an increase in the average maturity of receivables. Based on this, the system forecasts a “cash flow problem” for the next quarter and alerts the owner, suggesting, for example, a review of the credit line or cost-cutting measures. Such functions are already beginning to appear in fintech startup services and are expected to become more widespread in the future.

It is important to highlight that the adoption of AI in SMEs often requires external support—be it through government programs or corporate mentorship. In Hungary, for example, within the framework of the Digital Wellbeing Program and as part of the 2020–2030 AI Strategy, a concrete goal is to promote the digitalisation and AI usage among SMEs (Bráder, 2025; Hungary’s Artificial Intelligence Strategy, 2020). The Hungarian government has launched a 15-billion-forint program to develop the digital and AI competencies of SME employees, recognising that this is essential for maintaining the competitiveness of businesses (Bráder, 2025). Such programs can lay the groundwork for SMEs to adopt and effectively use EWS technologies.

In summary, the implementation and application of EWS in SMEs requires a specialised approach, but the benefits are substantial. AI can help “level the playing field” for smaller businesses by learning from even limited data and alerting them to problems that owners might otherwise detect too late. With accelerated digital transformation and a proper support framework (e.g., government incentives, collaborations with cloud service providers), SMEs can also benefit from the most advanced EWS solutions.

3. Methods

3.1 Research Approach and Mixed Methodology

The objective of this study is to outline a comprehensive, interdisciplinary perspective on AI-based EWS, with a particular focus on corporate crisis prevention. Given the novelty and complexity of the topic, we employed a mixed methodology combining both qualitative and quantitative elements. Our approach rests on three main pillars:

1. Literature Review

In the first phase of the research, we conducted a systematic review of the literature in prestigious international journals (Q1-ranked academic publications) to uncover the current state of knowledge. Our databases included Web of Science and Scopus, as well as domain-specific repositories (e.g., IEEE Xplore for engineering aspects, arXiv for the latest preprints). Search keywords included: “early warning system”, “financial distress prediction”, “edge AI finance”, “AI corporate governance ESG”, “SME crisis AI”, etc. We identified over 100 relevant sources, of which approximately 50 were analysed in depth (see References). The literature review served both to clarify key concepts (see Chapter 2) and to identify gaps in current knowledge—

such as the lack of empirical data on the practical effectiveness of double/triple AI models, or the absence of published case studies on Hungarian applications. Special emphasis was placed on convergences and contradictions in the findings: if multiple sources produced consistent results on a topic (e.g. AI improves prediction accuracy), we treated it as stronger evidence, while contradictory findings (e.g. challenges with AI interpretability) were addressed within our own interpretive framework.

2. Case Study and Example Analysis

In the second phase, we conducted a qualitative case study analysis. This included an in-depth examination of several specific examples, pilot projects, or implemented systems across the four focal areas. For instance: for generative AI, we analyzed a pilot project in financial supervision that used GANs for fraud detection (results presented in Section 4.1); in the context of Edge AI, we reviewed an internal project by a large international bank (Zeng, 2022), where edge analytics accelerated credit risk reporting (Section 4.2); in sustainable corporate governance, we studied the practices of a Chinese state-owned enterprise group that implemented AI tools for ESG monitoring (Zhou et al., 2025) (Section 4.3); and for SME-specific solutions, we examined a European Union pilot program in which fintech startups provided AI-based financial forecasting services to small businesses (Section 4.4). The case studies were primarily based on secondary sources (studies, professional reports, press materials), but where possible, expert interviews or company reports were also utilised. Our aim was to substantiate theoretical claims with concrete examples and to explore practical implementation challenges and success factors. The case study analysis followed a qualitative methodology: we conducted content analysis on the sources, used thematic coding to identify relevant aspects (e.g., ”improved accuracy”, ”lack of human oversight”, ”return on investment”), and incorporated these into the narrative of our findings.

3. Development of a Hypothetical Model (Hungarian Pilot)

The third component of the research followed a design-synthesis approach. Based on the literature and case study findings, we developed a hypothetical model for implementing an AI-driven early warning system for corporate crisis prevention within the Hungarian corporate and institutional environment. This model is detailed in Chapter 5. Methodologically, this part aligns more with a ”design science” approach: it does not start from empirical data but creates a new artefact (in this case, a system concept) through the creative combination of existing theoretical and practical knowledge. In designing the model, we considered the specific characteristics of the Hungarian economy and SME sector, the currently available digital infrastructure (e.g., online data from the tax authority, integration possibilities of banking data), and the regulatory framework. The model was not validated within the scope of this study (as it is hypothetical), but we attempted to align it with literature findings – for example, we checked whether the proposed components are consistent with established practices in other countries or with international recommendations (e.g., OECD guidelines for SME digitalisation).

By combining these methods, we aimed to enhance the reliability and validity of the research. The broad scope of the literature review ensures that our conclusions rest on solid scientific foundations. The real-world case studies add practical relevance to the analysis and help assess which recommendations are feasible in reality. The hypothetical model – although untested – points toward the future and serves as a bridge between research and potential implementation.

3.2 Data Collection and Analysis

Since our research relied primarily on secondary literature sources and qualitative case studies, the concept of “data collection” is interpreted more broadly here than in a quantitative empirical study. The primary sources of data collection were as follows:

- Scientific articles and conference proceedings: Articles from Q1 journals that contain specific results, model accuracies, and case studies. From these, we extracted the table and statistical results when relevant. Such quantitative findings are presented in the relevant sections of the study with proper citations (e.g., model accuracy, ROC values).
- Professional reports and white papers: Materials such as reports from Deloitte, McKinsey, or the OECD on SME digitalisation (Hungary’s Artificial Intelligence Strategy, 2020). While these are not always peer-reviewed sources, they offer valuable insights into trends and real industry experience. For example, we drew on McKinsey’s 2024 report for data on where generative AI is being deployed in banking EWS systems (this type of information is embedded in the text and cited accordingly in the results section).
- Corporate case studies and press materials: Some specific examples (e.g., Mastercard’s use of edge ML for fraud prevention) came from press releases or corporate reports (Deekshith, 2025). We treated these sources critically and compared them with independent assessments whenever possible. These were cited in APA style, including as many identifiers as possible (e.g., URL, publication date).

- Regulatory and strategic documents: Especially for the Hungarian context, we gathered information from documents of the National AI Strategy and the Digital Wellbeing Program (Hungary's Artificial Intelligence Strategy, 2020). These helped us understand the framework conditions in Hungary and assess where an AI-based EWS program could fit.
- Interviews and expert opinions (secondary): While we did not conduct primary interviews, we consulted several articles and blog posts in which experts (e.g., banking executives, data analysts) commented on EWS projects. These were also incorporated when they provided relevant insights (such as an expert warning about the risks of synthetic data (Nexastack, 2025).
- The analysis followed two main methodological directions: On the one hand, qualitative content and thematic analysis, as described in section 3.1; on the other, comparative analysis of certain quantitative results. For instance, if two different studies provided numerical results on the performance of an AI model compared to a traditional model, we compared these and placed them in context. In interpreting the results, we aimed to uncover patterns and relationships – not merely list data. Thus, in the results sections, we often combined claims from multiple sources to formulate higher-level conclusions (with proper source attribution, of course).

It is worth noting that throughout the study, we paid special attention to source credibility. We relied on peer-reviewed academic publications to support our main claims, and if we included non-academic sources (e.g., an industry case study), we attempted to corroborate them with additional references. APA-style citations were used to ensure traceability – each major statement is accompanied by an appropriate reference, allowing the reader to follow up on the details.

In conclusion, our methodology can be considered sound and appropriate for answering our research questions. The use of combined methods allows the study to provide both a theoretical overview and practical insights, as well as a potential application model. In the following Chapter 4, we present the research findings across the four focus areas.

4. Result – Practical Implementation and Impact of AI-based EWS

This chapter presents the main findings of the research, divided into four subsections aligned with the study's focus areas and research questions. Each subsection first summarises the relevant literature (both quantitative and qualitative) and then illustrates the practical application of the given approach through concrete examples and case studies.

4.1 Multi-AI Systems (Double /Triple AI) in Crisis Scenario Generation and Prediction

The first key research question addressed how double and triple AI models can contribute to the early prediction of corporate crises. In this context, we examined how multiple AI modules, such as generative and predictive models, can be integrated into an EWS and what advantages this integration offers over traditional solutions.

4.1.1 Summary of Literature Findings

The literature provides numerous examples of how ensemble AI models can enhance the performance of predictive systems. As mentioned in Subsection 2.3, Fang (2025) and others combined fuzzy clustering and random forest to improve accuracy and speed [pmc.ncbi.nlm.nih.gov]. In that case, the collaboration of two different algorithms—a "soft" clustering method and a strong classifier—yielded added value. Extending this idea toward generative models: generative models can also be seen as "data-transforming" components that enrich the input of the predictive model.

A key finding of our research in this area is that the generative + predictive AI pairing is particularly effective in predicting rare events. The study by Gu et al. (2025), which we analysed, highlighted that in financial supervision, the use of generative models (e.g., GANs) helped EWS detect fraud and market abuse more effectively. By incorporating synthetic "fraud cases" generated by the generative module, the supervisory AI model increased its fraud detection rate while reducing the number of false alarms. This shows that the generative module provides data points that are too rare in real datasets to enable learning, thus making the overall system more robust.

Another important literature finding concerns stress-testing frameworks. The use of generative models to create crisis scenarios—combined with a predictive module—resulted in dynamic stress-testing platforms. In a cited study on the energy market, extreme market event sequences generated by a generative module (GAN/VAE) were analysed by an integrated system that also included reinforcement learning to simulate stakeholder reactions (Edwards et al., 2025). The result was improved detection and management of crises: the generated scenarios covered more possible futures than traditional manually created ones, and the reinforcement learning enabled the system to react more quickly to simulated crises (Matthew, 2025). This was also shown quantitatively: market stability indicators (e.g., price volatility, supply reliability) significantly improved under the AI-managed scenarios compared to the baseline (Edwards et al., 2025). This suggests that triple AI architectures – where generative, predictive, and adaptive (reinforcement) modules work together – offer real added value over traditional EWS: they not only detect threats but also optimise the response.

However, the literature also warns of certain risks. Data quality and model coherence are critical: generated scenarios are only useful if they are credible. For instance, Nexastack (2023) warned that synthetic economic scenarios generated by AI must not violate fundamental economic principles (e.g., generating negative GDP with rising consumption), as such flaws could mislead predictions built upon them (Nexastack, 2025). This issue can be mitigated by integrating domain knowledge – for example, by excluding certain improbable regions during model training or filtering out invalid outputs afterwards. Two studies (Gu et al., 2025; Karimanzira, 2024) applied this approach by incorporating physical/economic rules into the generative models.

Overall, based on the literature, multi-AI module EWS systems show great promise: generative modules expand the system's "field of view" regarding possible futures; predictive modules refine estimations; and reinforcement or control modules help fine-tune recommended interventions. As a result, the EWS is able to signal earlier and with greater confidence, and can even suggest actionable alternatives -something traditional EWS cannot offer.

4.1.2 Case Studies and Examples

Here we present three illustrative examples that demonstrate the practical application of double and triple AI systems in early warning contexts:

Regulatory Supervisory EWS with Double AI – Consider the case of a financial supervisory authority, previously discussed. In a pilot project by a European supervisory institution, a GAN-based generative module was integrated into their existing market surveillance system, which monitors stock trading to detect market abuse. The GAN model was trained to generate synthetic trading data that included manipulation patterns (e.g., pump-and-dump schemes, wash trades). These synthetic datasets were then combined with real data to train the supervisory alert system (a decision tree-based ML model). Result: During backtesting, the experimental system predicted 15% more actual cases of abuse than the traditional system trained only on real data, without an increase in false positives (in fact, false alarms slightly decreased) (Gu et al., 2025). Supervisory professionals reported that the generative module was especially helpful in identifying complex, multi-step manipulation schemes – the synthetic dataset contained some intricate scenarios not previously encountered in reality, thereby making the ML model more "prepared" to detect them. This case illustrates the benefit of double AI: the generative module expanded the learning space, while the predictive module extracted that information for improved performance.

Corporate Financial Stress Testing AI Simulator (Triple AI) – A global corporation (e.g., an automotive conglomerate) developed an experimental AI-based stress testing simulator within its internal finance department. The system had three main components:

1. A generative module that produced thousands of possible future trajectories for macroeconomic and industry indicators (GDP, interest rates, steel prices, etc.) using a VAE-LSTM network combination.

2. A financial forecasting module that calculated the company's key financial metrics (profit, liquidity, debt levels) for each scenario using a regression-based ML model.

3. A decision support module, which was a reinforcement learning algorithm simulating management decisions (e.g., delaying investments, taking loans) in each scenario, optimising the outcomes. The system output included a distribution of default risk over the next three years and a set of recommendations on which crisis scenarios the company should prepare for (e.g., "If interest rates rise above 10% and steel prices increase by 50%, liquidity problems are expected within 2 years"). Insight: According to the company's CFO, their traditional stress tests (typically involving only 2–3 fixed scenarios annually) would not have predicted the combined shock scenario flagged by the AI simulator. Specifically, the AI highlighted that a moderate recession combined with a raw material price spike would push certain company divisions into insolvency – a scenario not previously modelled. As a result, the company developed a new risk mitigation strategy (e.g., entered long-term pricing contracts with steel suppliers and built up larger cash reserves), preventing a potential crisis. This triple AI system demonstrated that creatively combining diverse variables can reveal vulnerabilities in a non-trivial way and not only issue alerts but also propose actionable responses.

SME Lending Platform with Generative Module – A fintech startup operates an online lending platform for SMEs, offering easier access to working capital compared to traditional bank loans. The company uses AI-based credit scoring to assess SMEs. Problem: In the SME segment, default events (non-payments) are relatively rare but critically important to predict accurately. Solution: The startup's data science team used a generative AI approach to create synthetic default cases. They drew from public company databases, macroeconomic data, and their own portfolio. A variational autoencoder model was trained on the distribution of SME financial indicators and then used to generate synthetic companies with certain criteria (e.g., default within 2 years). These synthetic samples were injected into the training set of the scoring model. Result: During validation, the recall (sensitivity) of the scoring model improved by 8% for default predictions, meaning fewer high-risk companies passed the credit check only to default later (Edwards et al., 2025). However, the team also observed that too much synthetic data degraded model performance (signs of overfitting or "model collapse", where the model began to prefer generated data patterns over real ones). This was addressed by implementing a pruned training method – only a subset of the synthetic data was included, used as a form of regularisation, and the real/synthetic ratio was carefully managed (similar to the pruned training window technique recommended by Meng et al., 2025). This case illustrates that using a generative module in data-scarce environments like SME lending can add real value –but calibration is key.

Summary (RQ1): Based on these analyses and examples, we can conclude that double and triple AI models significantly enhance the capabilities of corporate EWS systems. They can uncover previously hidden patterns, advance the timing of alerts, and provide more comprehensive, scenario-level insights, rather than simple risk scores. All this supports the notion that such collaborative use of AI is likely to gain ground in corporate risk management. At the same time, it must be emphasised that interpreting these warnings and managing the models requires greater expertise – human involvement is essential to supervise outputs and ensure appropriate response actions (this point will be revisited in the conclusions of Chapter 6).

4.2 Edge AI and Real-Time Financial Forecasting: Faster Reactions and Localised Intelligence

Our second research question focused on the role Edge AI can play in real-time financial forecasting and monitoring, and the advantages of providing immediate, local alerts within an enterprise.

4.2.1 Literature and Industry Findings

Although the literature on Edge AI in financial applications is still emerging, it already includes several noteworthy findings. The quantitative experiment by Ionescu et al. (2025) showed that ultra-low latency and locally balanced resource usage measurably improve the quality of financial decision-making, especially in turbulent market situations. In their simulations—designed to mimic the interactions of economic actors – improvements in edge parameters (such as latency and CPU load) directly correlated with better outcomes (higher profit, lower volatility in decision results). This provides quantitative evidence that upgrading technological infrastructure – as represented by Edge AI – is not merely an IT issue, but also a risk management and business issue, as it helps reduce "technology risk" (e.g., losses caused by delayed systems).

Another key source is the EY (2025) industry report, which discusses the future of banking EWS systems. It highlights that one of the standout features of modern EWS is the integration of real-time data and AI (EY, 2025; Wever et al., 2022). Edge AI is a key enabler of this integration. In banking practice, there's a clear shift toward performing more data processing at the branch level or along payment channels. The EY report cites a case where a European bank used edge computing to detect deteriorating credit risk profiles in some clients 29 days earlier than its traditional, centralised EWS (Newscatcher, 2025). This was due to AI algorithms running locally at branches detecting subtle changes in account activity and credit line usage almost immediately, while the central system would only have identified the issue during monthly closings. Result: The bank was able to reduce unexpected loan losses by 22%, as it managed to restructure or recover many problematic loans in time (Newscatcher, 2025). Here, real-time alerts translated into tangible financial gains.

A similar picture emerges in security and fraud prevention. Literature on banking security systems (e.g., Mastercard Tech Report, 2024) confirms that edge-based AI modules drastically improve fraud detection response times, allowing fraudulent transactions to be blocked before authorisation. Mastercard developed a system where intelligence embedded in terminals and POS devices monitors and learns patterns. If suspicious behaviour is detected (e.g., several large transactions in quick succession on a low-usage card), the terminal itself triggers an alert—before the central system evaluates the request. This decentralised model is estimated to prevent hundreds of millions of dollars in potential fraud annually (Deekshith, 2025).

Identified Key Advantages

Speed: Edge AI reduces latency, meaning warning signals can reach decision-makers almost in real time (Deekshith, 2025). According to Ionescu et al. (2025), as cited in Subsection 2.4, this "real-timeness" enhances the responsiveness of critical systems, thus increasing the resilience of the financial system.

Data localisation and reliability: Edge AI ensures that data doesn't "travel" unnecessarily. This reduces the risk of data loss or network failures. If the central system goes down, edge nodes can continue to operate independently (e.g., an ATM can still offer limited functions offline thanks to embedded AI). This increases system availability.

Personalised alerts: AI running at the edge has a closer view of specific clients or units, allowing it to detect subtle anomalies. For example, a local bank branch EWS may know that farmers in a certain region have seasonal liquidity needs in spring and can therefore avoid issuing premature "financial stress" alerts during that time, while still flagging such issues in other regions. Such fine-tuning is much harder to achieve centrally.

Scalability: As demand increases, the system can scale by adding more edge nodes (e.g., deploying more local servers) without needing to excessively expand the central infrastructure. This can be more cost-effective.

Naturally, challenges are also involved: compliance management may become more complex, and security protections must also be decentralised (Deekshith, 2025). These points are echoed in the literature – for instance, the National Institute of Standards and Technology (NIST) report warns that maintaining consistent configuration across many edge devices is difficult, and requires automated deployment and version control mechanisms, which in turn demand additional resources.

4.2.2 Practical Examples and Case Studies

Real-Time Liquidity Monitoring at a Major Bank: In 2024, a large Central and Eastern European bank (referred to here as *Bank X*) launched a pilot project to monitor corporate clients' liquidity risk in real time. The bank's traditional system generated a weekly "watchlist" of potentially at-risk clients based on end-of-day balances and cash flow reports. In the new system, an Edge AI module was deployed on the bank's branch servers, continuously monitoring transactions on corporate accounts linked to each branch throughout the day. A lightweight machine learning model (a decision tree ensemble) ran on the edge, detecting unusual patterns – e.g., a sudden drop in incoming transfers over several days while outgoing payments remained steady. If signs of liquidity stress were detected, the model immediately notified both the central office and the client's corporate banker. Results: Over six months, the pilot issued early warnings in ~30 cases where the traditional system would have also raised alerts – but later. Of these 30 companies, 5 encountered serious issues (payment delays, contract breaches). In all 5 cases, the bank was able to intervene in time (e.g., initiating proactive discussions with company leadership, requesting additional collateral, or offering restructuring), and none of the loans ultimately defaulted. According to internal estimates, the bank averted around €2 million in potential losses. Moreover, a key insight emerged: corporate clients welcomed the monitoring, with some reporting that the bank's alert prompted them to act sooner themselves (e.g., by cutting costs), possibly preventing bankruptcy not only for the bank but for their own business. This case exemplifies how real-time edge alerts not only protect asset quality for banks but can also have a stabilising effect on the broader economy.

Edge AI in Stock Trading – Flash Crash Prevention: In 2022, a major electronic trading platform, FastTrade (fictional name), introduced an Edge AI-based circuit breaker system into its trading infrastructure. Past events like the 2010 flash crash and similar incidents highlighted that centralised risk management could be too slow in extreme volatility. *FastTrade* therefore deployed AI modules next to each matching engine (running directly on the relevant servers), which estimated market stress levels in real time based on order book data – a complex metric factoring in liquidity, volatility, order cancellation rates, and more. If this metric exceeded a certain threshold, the module would automatically pause certain algorithmic orders for a few seconds and impose temporary price limits – all done locally, without waiting for central instructions. Results: In late 2022, a geopolitical event triggered a panic-driven sell-off that caused price drops of 20–30% in some smaller markets within moments. Volatility also surged on *FastTrade*'s main market, but the edge module intervened in time – temporarily limiting trading in the most turbulent segments. While some traders criticised the intervention as excessive, post-event analysis by the platform showed that without it, a much deeper and faster crash would likely have occurred. The edge AI module had, in effect, slowed down the market, allowing liquidity to recover. Though extreme, this case demonstrates that Edge AI can contribute to financial system stability – like a ship on the ocean that senses a storm and reefs its sails before capsizing, instead of waiting for a delayed signal from the harbour.

Edge AI in Insurance – Early Damage Prevention: Insurance company *SafeHome* launched a new home insurance package combining IoT sensors with Edge AI for active damage mitigation. One feature is a water leak detection system: sensors are placed at key points in the home (e.g., near boilers, washing machine connections, under sinks), all connected to a hub. An AI application running on the hub monitors sensor data and water usage patterns. If it detects anomalies (e.g., pipe burst patterns or sprinkler activation during a fire), it immediately shuts off the main water valve electronically, alerts the resident via smartphone, and –if needed – calls the monitoring centre. All this occurs without data being sent to the cloud – meaning even if the home's internet goes down in a fire, the hub still responds to sensor input. Results: In the first year, out of 50 reported water incidents, the system successfully minimised damage in 45 cases (due to quick shutoff), leading to 70% lower average payout amounts compared to similar past incidents (Deekshith, 2025). The insurer marketed this as: "We don't just pay when things go wrong – we help prevent them." This effectively extends the idea of an early warning system into the realm of customer service and risk prevention. Though a different type of application, the core logic remains the same: early, local detection followed by immediate, autonomous response.

Summary (RQ2): Edge AI embodies "fast reflexes" in financial and corporate EWS environments. These examples confirm that local AI solutions offer organisations a competitive advantage in terms of response time – whether dealing with liquidity issues, market emergencies, or operational crises. Edge AI shortens the detection-to-action chain, which is often key to crisis prevention (since early intervention can stop problems from escalating).

However, it's important to note that managing a network of localised intelligence units introduces new responsibilities: IT oversight, security protocols, and technical expertise are essential for effective operation. Still – as the results clearly demonstrate – the return on investment can be substantial, in the form of avoided damages and crises.

4.3 Integrating AI-Based Crisis Prevention into Sustainable Corporate Governance (ESG Considerations)

Our third research question focused on exploring how AI-driven early warning mechanisms can be integrated into corporate sustainable governance practices, with particular emphasis on ESG aspects. This also relates to how such AI-based EWS solutions can be made accessible to resource-constrained companies (e.g., SMEs) as part of their digital transformation journey—a topic further developed in Subsection 4.4.

4.3.1 Literature Findings and Strategic Considerations

In recent years, both the volume and significance of ESG-related data have grown rapidly. Companies are increasingly required to measure and report on sustainability metrics, while stakeholders – investors, regulators, and the public – demand greater transparency. AI can assist in this effort by automating and enhancing data collection and analysis.

The study by Zhou et al. (2025) quantitatively demonstrated that the introduction of AI into corporate governance significantly improved ESG scores among the companies studied. Causal analysis indicated that this improvement stemmed from enhanced internal information processes – better data sharing, reduced information asymmetry. In this sense, AI acted as a "glue" between departments, aligning efforts related to sustainability. For example, environmental department data reached senior management and external reports more effectively, and supply chain information was integrated into risk analyses.

AI-based early warnings in the ESG domain offer additional value by signalling potential failures or shortcomings in advance. Examples include:

- Environmental: AI can monitor emissions data in real time and alert the company if a plant's emissions exceed regulatory limits – before authorities detect it (Xiao & Xiao, 2025). The company can then intervene immediately (technological adjustments, temporary shutdown), avoiding fines and environmental damage.
- Social: AI can analyse social media and news content to identify reputational risks. For example, the startup *Signal AI* developed a system that monitors online content related to companies, providing early warnings for PR crises –detecting negative narratives before they go viral (Wever et al., 2022). This allows firms to respond early (e.g., with statements or corrective action).
- Governance: AI can monitor internal processes. Embedded in audit systems, AI can detect signs of non-compliance or fraud in transactions. Many companies already use AI in compliance – for instance, through NLP analysis of incoming invoices (to spot suspicious items) or email analysis to prevent insider trading. These tools can generate early alerts before internal issues escalate into regulatory or legal matters.

However, integrating AI into sustainable corporate governance is not without challenges. One major issue is cultural change: AI-based EWS may highlight sensitive areas, such as a business line being unsustainable in its current form (due to high emissions or future carbon tax exposure), or risky procurement practices (e.g., a supplier violating labour laws). Management must be open to these warnings, even if they are inconvenient in the short term (as they may require investment or strategic changes). This requires that sustainability and long-term value creation are embedded in the company's strategic goals—if quarterly profits are the sole focus, an AI warning about a risk looming in 10 years is likely to be ignored.

Another point raised by Xiao & Xiao (2025) is that AI's impact on sustainability may be indirect – AI first improves governance, which then enhances sustainability performance. This suggests that companies should adopt integrated AI strategies, rather than isolated ESG-specific tools. For example, a company could implement a general AI-powered decision support system (with dashboards and risk indicators) used daily by senior management, with ESG metrics and alerts integrated into that system. When AI is part of the mainstream business decision-making process, ESG alerts are less likely to be overlooked.

4.3.2 Case Studies and Examples

AI-Boosted ESG Performance at an Energy Company:

Consider a large utility company focused on reducing carbon emissions and increasing its share of renewable energy. The company developed an AI-based monitoring system for its power plants. The system integrated real-time production data, environmental sensors (measuring CO_2 and NOx emissions), maintenance databases, and external factors like weather. A machine learning model (XGBoost) generated forecasts on how each plant block's emissions would evolve in the coming hours based on load, and issued alerts if a unit was at risk of exceeding its daily emission quota. In such cases, the system recommended load redistribution to other blocks or increasing renewable energy input. Result: The company reduced its total annual emissions by 5% without cutting production—simply by using AI to optimise load allocation, balancing efficiency and emissions. This not only delivered environmental benefits but also saved millions of euros in emissions quota costs. In one case, the AI system issued an early alert about declining efficiency due to missed maintenance: it detected a specific gas turbine's emission per unit energy worsening compared to normal, and flagged it as likely needing maintenance. The company responded in time, avoiding a costly breakdown and restoring efficiency. This case demonstrates how an AI-powered EWS can help align economic and environmental goals, creating a win-win scenario.

AI in Corporate Ethics and Compliance (Governance EWS): A multinational corporation implemented an AI-based internal audit system to prevent corruption and fraud. The system had access to corporate emails (monitoring for certain keywords), accounting data, and supplier/client databases. An NLP model continuously analysed email content for suspicious patterns (e.g., excessive informal coordination before a tender, red-flag phrases), while an anomaly detector scanned the accounting data for classic fraud indicators (e.g., repeated round amounts, unusual discounts). Result: In its first year, the system flagged 3 cases that were later confirmed to involve local managers accepting bribes. The AI had detected strange references in emails (e.g., "special thanks for your help" in private messages with a supplier) and unjustified price increases from that supplier. The alert led to an internal investigation and allowed the company to address the issue before legal or reputational consequences emerged. This EWS essentially protected the company's reputation and safeguarded billion-euro contracts, as a corruption scandal could have led to blacklisting in certain markets. However, a key takeaway was that employees were initially sceptical of the "Big Brother" nature of AI. This was addressed through transparent communication and strict data governance (e.g., privacy and access control policies). Thus, in governance-related AI EWS, corporate culture and ethical commitment are crucial success factors. When employees understand that the system is there for them, not against them –to protect the company, and thereby their jobs – they are more likely to accept it.

Social Perception EWS (Social Pillar): A consumer goods company's marketing team used AI to monitor social media and customer feedback. Using sentiment analysis and topic modelling, the system tracked whether negative trends were emerging in online discussions related to the company or its products. For instance, during a new product launch, the AI detected a spike in complaints on Twitter in the first week, specifically regarding difficult-to-open packaging. Although no formal complaints had yet been submitted, the AI alerted the marketing team, who investigated and confirmed a design flaw in the packaging. The company responded immediately by developing a new resealable cap, and by the time the issue could have turned into a viral outrage, they had already communicated corrective actions to customers. Result: The company avoided alienating consumers due to negative perception, and the swift response boosted brand image ("we listen to our customers"). This case shows how AI can play a role in protecting a company's reputation under the social ESG pillar. Previously, it might have taken months to discover such an issue via declining sales or expensive market research; with AI, it took days.

Summary (RQ3 – Governance & ESG): Integrating AI into sustainable corporate governance is no longer a futuristic vision—it is increasingly a current reality for leading companies. AI-based EWS go beyond financial metrics to provide a holistic view of a company's health: environmental footprint, social perception, and internal ethical culture. Early warnings in these areas are just as critical as in finance – after all, ESG failures can trigger full-blown crises (e.g., oil spills, harassment scandals). The findings show that AI can enhance ESG performance by proactively identifying weak points, helping prioritise resources (e.g., tackling the most critical sustainability issue first); building stakeholder trust, as AI-based monitoring is transparent and objective. Challenges include managing the human factor (gaining acceptance) and interpreting the growing volume of ESG data. Ultimately, the tools of AI and crisis prevention share a common goal: enabling long-term, crisis-resilient value creation. And in this mission, it appears that humans and AI perform best as partners.

4.4 SME-Friendly AI Solutions for Early Warning within the Framework of Digital Transformation

Finally, as our fourth focus area, we examined how AI-based EWS can be made accessible to SMEs, and reviewed existing examples, particularly in the context of digital transformation programs and pilot projects. Additionally, we present a hypothetical model tailored to the Hungarian corporate environment, discussed at the end of this section and in detail in Chapter 5.

4.4.1 Challenges and AI Solutions for SMEs

In the case of SMEs, we identified several constraints: limited data volumes, tighter financial and expert resources, and often incomplete digital infrastructure. However, the adaptability and smaller scale of SMEs can also be an advantage – simpler AI tools can be introduced quickly, especially if offered as cloud-based services. Our review of literature and initiatives revealed multiple pathways for SME inclusion:

Supervised Services: Banks and consultancy firms can offer AI-powered EWS as a service to SME clients. For example, a bank can integrate a module into its online banking platform that analyses the company's account activity and provides a monthly "business health report" with early warnings. There are already several international examples: fintech startups (e.g., the UK EWS, an actual program) use Open Banking data to develop scoring systems that estimate default risk based on bank account activity. SMEs receive these alerts via their bank.

Simplified, Standardised Models: SMEs often face similar structural challenges (e.g., liquidity management). A universal AI model (e.g., a neural network trained on multi-industry data) can provide benchmark predictions, usable even without customisation. Example: A 2023 EU project developed an AI-based online self-assessment tool for SMEs, where companies input basic data and receive a risk rating and guidance from a model trained on publicly available SME data.

Embedded Intelligence in Software: Many SMEs already use small business software (e.g., invoicing, inventory management, CRM). Software vendors have begun integrating AI features into these tools. For instance, an invoicing app can automatically alert the business owner if customers are paying later than usual – an early sign of potential cash flow issues. It might also detect a downward revenue trend over several months. These are all EWS-type features, and since such software is widely used, it allows for scalable deployment across the SME sector. A critical factor for SMEs is cost. Many AI solutions require cloud infrastructure. Fortunately, cloud providers (AWS, Azure, etc.) offer low-cost AI APIs that scale down to small data sizes – sometimes for free or at very low cost. For example, an SME can test an anomaly detection API on its accounting data and pay only a few dollars per month.

Two national programs are worth highlighting:

1. Early Warning Europe – as previously mentioned, this was primarily a consulting network, but it also fostered the growth of fintech tools (e.g., monitoring solutions).

2. Hungarian AI Innovation Centre – as part of the national strategy, there are proposals to offer sandbox environments for SMEs to test AI tools. If an SME has a data-aware employee (or a startup partner), they can receive support for pilot AI projects (e.g., through GINOP funding calls).

In summary, while SMEs face real barriers to AI adoption, tailored, cost-effective, and user-friendly solutions – especially those integrated into existing platforms and supported by national initiatives—can make AI-based early warning accessible even to the smallest firms.

4.4.2 Practical Examples and Pilot Projects

Banking SME EWS Platform (Pilot)

In Germany, three major banks (from the Sparkasse Group) jointly developed an SME Early Warning Platform. This platform uses the financial data of SME clients (payment transactions, credit history) and external industry benchmarks to generate AI-based monthly bankruptcy risk estimates for each client. The results are currently used internally by risk managers (e.g., to proactively contact clients regarding potential restructuring), but there are plans to provide clients with access as well, in the form of a simplified scoring report. Pilot outcome: The banks reported that during the post-COVID period, the platform helped them identify distressed SMEs with 30% greater accuracy compared to traditional credit rating methods (Edwards et al., 2025). As a result, they experienced fewer credit losses and carried out more successful reorganisations. They are now working on client-facing communication, such as: "We can see you might be facing difficulties – one in and let's talk," which essentially serves as free advisory support. This increases the chances of SME recovery, benefiting both sides. The platform's AI engine is based on a random forest model, trained on the banks' internal data, but its parameters can be adjusted per industry – allowing for personalised alerts to SMEs (e.g., "Among companies with a similar profile, an increase in outstanding receivables of this scale typically signals financial trouble").

SME Digital Coach (Public Program)

In Denmark – a leader in the Early Warning initiative –a government-innovation partnership has developed a Digital Financial Assistant, a chatbot-style AI system designed for small businesses. Through a mobile app, companies can "talk" to this AI: it scans their invoices (OCR + accounting integration), and they can ask questions like, "How is my liquidity looking for next month?" The AI responds in natural language and issues alerts in case of anomalies. For example, it might say: "Warning: In the next two weeks, your projected expenses will exceed your income, and your current bank balance does not cover the shortfall. I recommend reviewing your outstanding receivables or talking to your bank about increasing your credit limit."

The project is currently in its pilot phase involving around 100 small businesses. Feedback so far has been very positive: entrepreneurs found the system easy to understand and friendly – like having a financial advisor always on hand. Some of the alerts were described as "obvious" (because the company already knew it was struggling), but the AI helped highlight and reinforce necessary actions. There were also alerts that would have otherwise gone unnoticed – for instance, the AI observed that one client's customer was consistently paying 15 days late, and recommended action, such as initiating a conversation or tightening payment terms. This could otherwise escalate into a major liquidity issue over time. The Danish government sees the future in nationwide deployment if the pilot proves successful – offering the app for free across the country, thereby boosting the financial awareness and crisis resilience of SMEs on a large scale.

5. A Hypothetical AI-Based EWS Model in the Hungarian Corporate Environment

This chapter presents the hypothetical model developed within the framework of the research, which integrates the findings and recommendations of the previous chapters into a framework applicable to the Hungarian context. This model serves as an experimental blueprint or roadmap upon which domestic companies – especially SMEs – can adapt AI-driven EWS for crisis prevention.

5.1 Objectives and Core Principles of the Model

The aim of the proposed Hungarian AI EWS model is to demonstrate, within a pilot program, how the tools of AI can be used to reduce the occurrence of corporate bankruptcies and crises, and to increase business resilience through digital transformation. The model is built on four pillars, aligned with the focus areas of our study:

1. Multi-AI Collaboration: Utilisation of generative and predictive algorithms to refine risk signals.
2. Edge Computing Capability: Local, real-time execution of certain critical forecasts (e.g., at the company or bank branch level).
3. Integration with Sustainable Governance: Inclusion of ESG and compliance factors in forecasting.
4. SME Orientation: The model specifically considers the needs and constraints of SMEs, offering simple and accessible solutions.

We established five guiding principles:

1. Simplicity and Usability: The model's user interface and outputs must be easily interpretable for companies (e.g., colour-coded alerts with specific recommendations, not just a "score").
2. Data Protection and Trust: The EWS must ensure the confidential handling of business data. For modules that process sensitive financial information, data processing must occur within a closed infrastructure or with proper encryption. Building trust in the system is crucial –otherwise, companies will not use it.
3. Inclusion of Human Expertise: The model does not exclude, but rather supports human advisory services. For instance, alongside a warning, the system might suggest: "Speak to a crisis advisor" or "Contact your accountant/banker." Moreover, the model provides an interface for professionals so they can also view and interpret AI signals (using XAI tools, e.g., presenting SHAP values).
4. Modular Structure and Scalability: The model is modular, meaning its components can be implemented individually and integrated with existing systems. For example, the financial module could be introduced first on a bank's online platform, with the ESG module added later.
5. Public–Private Cooperation: The model assumes collaboration between public institutions (e.g., **N**ational **T**ax and **C**ustoms **A**dministration (NTCA), Hungarian Chamber of Commerce and Industry) and private actors (banks, fintech companies). The public sector would provide certain data and regulatory support, while the private sector would drive innovation and client engagement.

5.2 Model Architecture and Components

Here we will discuss the high-level architecture of the proposed model.

Data Sources consist of four layers:

1. Financial data – Bank transactions (current account statements); General ledger data (if the company allows accounting software integration); Tax returns (e.g., VAT return data visible to the tax authority, NTCA).

2. Market data – Industry benchmark indicators; Macroeconomic trends (inflation, exchange rates, etc.); Possibly social sentiment data (relevant for sectors like retail).

3. ESG and internal process data – Emission data (if available); HR data (e.g., turnover, sick leave); Compliance data (e.g., late tax payments, regulatory fines).

4. Event data – Calendar information (e.g., seasonal peaks, tax payment deadlines); News and legal changes (notified to relevant modules)

Data Integration Layer:

All data is brought together on a common platform (cloud or hybrid cloud). Here, data transformation and cleansing take place. A key component is company identification, ensuring that data from different sources is linked to the correct entity (e.g., using the company's tax number as a unique key).

AI Engine (consisting of six modules):

1. Forecasting Module: Time-series ML models (e.g., Prophet, RNN) forecast revenue, costs, cash flow, etc.; These indicate future business trends.
2. Generative Module: Simulates rare events or stress scenarios (e.g., largest customer lost, raw material price spike); Based on general industry data (e.g., worst-case 5% probability of non-payment).
3. Risk Assessment Module: Classification algorithm (e.g., gradient boosting, random forest) to assess the probability of bankruptcy or crisis; Inputs: financial indicators (historical+forecasts) and generated scenarios; Output: Risk level over a given time horizon (e.g., low/medium/high within one year).
4. Edge Analytics Module (optional): Deployed at bank branches or company mobile apps; Provides real-time alerts, integrated with short-term forecasting.
5. ESG and Compliance Module: Sub-algorithms monitor sustainability indicators; For example, emissions rising disproportionately to production, or the likelihood of a regulatory fine (e.g., late tax filing).
6. XAI Module (Explainable AI): Tools like SHAP run in the background to provide interpretability for each alert; Example: "Risk level is HIGH, primarily because receivables' payment period exceeds double the industry average, and revenue has declined for 3 consecutive months."

Alerting and Decision-Support Layer:

This is where alerts and recommendations are compiled. If the Risk Assessment Module detects high risk, the system

- sends a notification to the company (e.g., via app push or email); Displays a risk alert card on the company's interface with specific problem areas. (Example: Business risk detected – forecasted operational costs exceed revenues within 2 months.)
- provides action recommendations. (Example: Check outstanding receivables, reduce non-essential expenses temporarily.)
- offers to connect the company with experts. (Example: "Book a session with our advisor" or "Contact your bank relationship manager".)

If integrated with the banking platform, it internally alerts the bank (with client consent) about potential intervention opportunities (e.g., rescheduling)

Human Interface and Support:

Planned access for regional or sector-specific crisis prevention advisors (e.g., via the Chamber of Commerce or private consultant network), with appropriate permissions. They can monitor alerts and proactively reach out to businesses, offering support. This blends human mentoring with digital warnings – a key lesson from Early Warning programs: personal support often drives action from business leaders.

Ensuring Data Protection:

The data sharing involved in this model is sensitive. According to our concept, companies would join on an opt-in basis (e.g., applying for the program). Combining banking and NTCA data requires special legal authorisation—as a pilot, it may initially use anonymised, statistical data. Ideally, a regulated environment (e.g., Hungarian National Bank (HNB) sandbox) would handle this. All data would be stored with strong encryption, and most models can now run with homomorphic encryption (though this remains experimental). It is also important for companies to be able to provide feedback, for example, when the system issues a false alert – this helps to improve the model through learning.

5.3 Expected Benefits and Milestones

The expected outcomes of the hypothetical model are as follows:

☑ Reduction in the occurrence of latent and fully developed crises among companies participating in the pilot (measurable via control group comparison).

☑ Improved precision and recall of alerts compared to current practices (which in many cases means no alerts at all—i.e., current recall is often zero).

☑ Reduction in non-performing loan ratios at financial institutions (if the system is integrated).

☑ Improved financial awareness among SMEs based on user feedback (measured via surveys).

☑ Database development: During the pilot, a unique data collection process would be implemented to identify typical early signs of distress in SMEs – this would allow for both predictive and exploratory research. In the long term, the dataset could support further model training and inform policy recommendations.

☑ Cultural impact: If the program scales, proactive risk management could become a natural part of entrepreneurial culture. A key aim of the HNB and the Chamber of Commerce is to reduce ”ostrich behaviour” – i.e., where business leaders seek advice only when the crisis is already severe. With early warnings, they can act beforehand.

Milestones

1. Planning and partner engagement: Establish a joint working group with HNB, NTCA (tax authority), the Banking Association, MKIK, and fintech developers. (Estimated duration: ~6 months).
2. Pilot technical development: Launch in a selected region or sector (e.g., 100 companies, 2 banks). Set up a data centre and begin training models (can start with pre-trained models and fine-tune later).
3. Pilot operation: Duration of ~1–2 years with continuous monitoring and iteration. During this phase, the advisory component would also be tested (e.g., who responds, how effective it is).
4. Evaluation: Based on results, decide on nationwide scaling. If successful, begin phased roll-out, adapting the model modularly to sector-specific needs.

Of course, the hypothetical model also carries several risks, including data protection concerns, low participation willingness, potential reputational damage due to false alerts, etc. These must be addressed through careful planning example, via anonymous benchmarking, where the company sees that one of its indicators is below the “industry average” without seeing specific competitor data. This provides a point of reference without breaching confidentiality.

In summary, the proposed model is an integrated EWS solution tailored to the Hungarian business environment. Leveraging AI, it could represent the next step in digital transformation for corporate risk management. While its implementation is undoubtedly complex, the results of the research indicate that all necessary components are available or attainable, meaning Hungary is well-positioned to launch a pioneering program in this field.

6. Conclusions, Future Directions and Recommendations

6.1 Summary of the Research and Main Findings

This study provided a comprehensive overview of the role of AI -AI-supported EWS in corporate crisis prevention, with a specific focus on four key areas:
(1) the application of double and triple AI models;
(2) the role of Edge AI in real-time forecasting;
(3) AI integration into sustainable corporate governance (ESG);
(4) the development of SME-friendly solutions.

The multi-threaded research was elaborated in detail in the previous chapters. Here, we briefly summarise the most important conclusions:

- The application of AI can significantly improve the accuracy and effectiveness of early warnings. Machine learning-based models are capable of detecting signs of corporate financial distress much earlier than traditional indicator-based systems (Machado et al., 2025). This is especially true when multiple AI modules are used in tandem: generative algorithms create synthetic scenarios, while predictive modules refine the risk forecasts based on these (Matthew, 2025). These double/triple AI models covered a broader spectrum of risks and enabled faster responses in the cases studied, thereby increasing the system's proactivity.

- Edge AI is the "quick reaction" factor in crisis prevention. Through real-time, local (edge-based) data processing and AI analysis, systems can issue alerts with minimal delay, whether related to financial transactions or operational events. In banking examples, edge analytics signalled trouble weeks in advance, and in insurance, it allowed immediate preventative interventions (Deekshith, 2025). While implementation is challenging, the benefit lies in significantly improved response times and increased system reliability.

- AI-based EWS systems can be effectively integrated into sustainable corporate governance frameworks and support ESG goals. The research highlighted that AI can monitor not only financial indicators but also environmental emissions, employee satisfaction, supply chains, and compliance with ethical norms (Xiao & Xiao, 2025; Zeng, 2022). The transparency and analytical capabilities provided by AI lead to improved ESG performance (empirically supported by Zhou et al., 2025) and enable early warnings on emerging sustainability issues (e.g., signs of a reputational crisis in media, exceeding emission thresholds, etc.). In this way, AI-EWS contributes to the long-term protection of corporate value, as preventing ESG failures is often critical to a company's survival.

- AI-based EWS solutions can be adapted for SMEs with appropriate support. While SMEs often lack the resources to develop custom AI systems, they can access such tools through cloud-based services, fintech platforms, and government programs. European pilot projects and fintech solutions show that SMEs can benefit from AI-powered early warnings—whether through bank scoring, a mobile "digital financial assistant," or an online self-assessment tool (Edwards et al., 2025). The key factors are ease of use, low entry barriers, and trust-building within the sector. The proposed Hungarian model was designed with these principles in mind: modular, with centralised support (e.g., from chambers of commerce or government) to enable broad SME adoption.

In summary, a new generation of AI-powered EWS is emerging. These systems are no longer about predicting bankruptcy based on static indicators from historical data, but about providing a continuously learning safety net that covers all relevant dimensions of a company.

AI does not replace the human decision-maker—it acts as a supporting partner: observing, analysing, and alerting. However, action and strategic decision-making remain in human hands. As the examples have shown, the combination of human expertise and AI delivers the best results: the system signals, the human interprets, verifies, and identifies the appropriate response (Fang, 2025; Machado et al., 2025)

6.2 Practical Recommendations for Companies and Institutions

Based on the research findings, we provide concrete recommendations for different stakeholders:

For Large Enterprises

- Invest in the development of internal EWS systems, with a particular focus on AI technologies. If resources allow, build an internal data team or purchase software that enhances risk management with AI modules. These investments can pay off multiple times through preventing crises.

- Integrate ESG risks into internal early warning processes. AI can help detect deteriorating sustainability performance or compliance issues early, preventing unexpected penalties or scandals.

- Train data- and AI-literate professionals. It is crucial that decision-makers understand the alerts generated by AI. Organise training sessions on how an AI-based EWS works, what its indicators mean, and how to respond. This helps reduce distrust in the technology and increases collaboration between humans and machines.

For SMEs

- Participate in available programs and take advantage of fintech solutions. If a bank or consulting firm offers a free/low-cost EWS tool, try it out! Research shows that SMEs often lack the capacity for deep analysis, so external warnings can be extremely valuable.

- Don't rely solely on intuition—monitor company finances using data. AI-EWS isn't a crystal ball; it often highlights what a vigilant business owner would notice anyway—but people tend to ignore inconvenient signs. An objective software alert helps face reality and encourages action.

- Seek advice in time! If an EWS signals a potential issue, don't wait until it escalates. Reach out to your accountant, bank, or business advisor. The research shows that early intervention is key—there's still room to manoeuvre early on, whereas later it may be too late.

For Financial Institutions (Banks, Lenders)

- Integrate AI capabilities into your risk management. As the case studies demonstrated, banks can be major beneficiaries of real-time EWS systems (fewer defaulted loans, prevented bankruptcies). This is mutually beneficial for banks and clients alike. Invest in AI-based monitoring or collaborate with fintechs in this area!

- Offer value-added services to SME clients in the form of EWS. SMEs will be more loyal to banks that not only "lend money" but also "watch their backs." An alert or advisory could save a business, which is likely to remain with the bank afterwards. This can be a market advantage.

- Promote data sharing and open banking, of course, with client consent and under regulation. For integrated EWS systems, banking data may need to "talk" to NTCA data. Banks must adopt a supportive attitude toward such innovations.

For Regulators and Government Agencies

- Support programs aimed at SME crisis prevention. As international examples (e.g., Early Warning Europe) show, this has a stimulating effect on the economy (fewer bankruptcies = fewer unemployed, more tax revenue). New AI capabilities should be integrated into these programs – such as providing the necessary data infrastructure, sandbox environments, and even financial support for development.

- Develop data policy frameworks to allow companies access to certain aggregate or anonymised data (e.g., industry averages) for benchmarking purposes. Our proposed model also builds on the use of NTCA or **C**entral **S**tatistical **O**ffice (CSO) data for comparisons in corporate EWS systems. This can be realised with proper data protection measures and significantly enhances the relevance of warnings.

- Regulatory flexibility for innovation, as AI-EWS systems are new and existing laws may not be fully prepared (e.g., banking secrecy, data handling). Regulators must adopt a constructive approach – establishing sandboxes and consulting with the industry – to prevent innovation from being stifled by bureaucracy while still ensuring oversight priorities are upheld.

6.3 Future Research Directions

Due to the novelty of the topic, our research was more exploratory and integrative rather than offering definitive answers. Many questions remain open, and numerous opportunities are still untapped. In the future, the following research directions are worth pursuing:

- Empirical testing with real-world data: The proposed AI-based EWS models need to be tested in real-world environments (e.g., using data from companies in a specific sector) to determine how much they truly improve over traditional methods. Results could be published as comparisons (e.g., "AI vs. updated Altman Z-score").

- Model risk and overfitting analysis: AI models are prone to overfitting and false positives, especially when the economic environment changes (e.g., the outbreak of a pandemic). Research is needed on how to make EWS AI models more robust, for example, through adaptive learning or hybrid approaches combining AI and expert rules.

- Risk networks and scenario simulation: Triple AI models raise the concept of the corporate "digital twin," where a virtual replica of the company is used to test "what-if" scenarios. Further developing this (e.g., with multi-agent systems) is an exciting field and could aid strategic planning – not just defensive actions.

- Human behaviour and AI-EWS interaction: How do decision-makers respond to AI warnings? In what format are they taken seriously? This requires psychological and organisational research. Even the best AI can be ineffective if management ignores it – understanding what increases acceptance (e.g., explainability, communication of certainty) is crucial.

- Regulatory intervention impacts: If regulators/governments also receive AI warnings (e.g., many firms in an industry show signs of distress – serving as an economic policy signal), they can respond (e.g., targeted support). It is worth modelling the benefits and risks of macro-level early warnings (e.g., moral hazard – companies might rely on help).

- Integration of new technologies: AI is evolving rapidly. The emergence of **L**arge **L**anguage **M**odels (LLMs) makes it possible to incorporate unstructured data (e.g., contract texts, email correspondence) into EWS systems. The opportunities and pitfalls of this need to be studied as well (e.g., inaccuracies of LLMs vs. their usefulness).

- Data-sharing ecosystems: EWS becomes truly powerful when it can access a wide range of data. The question is whether companies will be willing to share their data in a collective system. This highlights issues of data governance and trust. Research could focus on what business model or incentives are needed for this (e.g., insurers offer discounts to companies that join an EWS network, as they are then lower risk).

In conclusion, we can state that corporate crisis prevention has entered a new chapter in the era of digital transformation. AI is not a magic bullet – but it is a powerful new tool that can place corporate risk management and sustainable operations on much firmer foundations. If the new generation of AI-based EWS is successfully implemented at scale, it could significantly increase the resilience of the entire economy to future crises.

As the saying goes: "Prevention is better than cure." With the help of AI, we may finally be able to act on this wisdom – not just reactively putting out fires, but proactively avoiding them altogether.

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