Artificial Intelligence in Early-Warning Systems: Opportunities and Challenges for Financial Risk Monitoring

Author: David Bowenkamp
University of Twente
P.O. Box 217, 7500AE Enschede
The Netherlands

ABSTRACT,
This thesis explores how artificial intelligence can strengthen early warning systems in the finance sector, which are necessary for detecting market risks. Since traditional systems use standard indicators and simple models, they often miss to detect complex risks due to the fast-changing markets. By reviewing recent research and drawing on survey responses, the study finds that new AI techniques like machine learning can identify risk patterns earlier and more accurately, especially when using diverse data sources such as news or market sentiment. However, most organizations are still at the testing stage, facing challenges around transparency, regulation, and expertise. For successful adoption, managers should focus on improving data quality, clear model explanations, and staff training. Ultimately, the value of AI-driven early warning systems will rely as much on careful management as on the technology itself.

During the preparation of this work, the author used "ChatGPT" in order to translate and for advice on text structure as well as inspiration for survey questions. Furthermore,"Grammarly" was used to check spelling and grammar. "Apple Intelligence" was used to enhance vocabulary by searching for synonyms. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

Graduation Committee members:
1st Supervisor: Dr. M.R. Machado
2nd Supervisor: Dr.Ir. W.J.A. van Heeswijk

Keywords
Artificial Intelligence (AI), Machine Learning (ML), Early-Warning-System (EWS)

1. INTRODUCTION

History has shown that financial crises have caused significant economic disruptions, often because potential risks were not detected early enough. For example, the Great Depression of 1929, the dot-com bubble in the year 2000, the global financial crisis from 2007–2008, and the COVID-19-related market disturbance in 2020 all highlighted the need for timely identification of financial instability (Romer, 1990; Shiller, 2000; Gorton, 2012; International Monetary Fund, 2020). To address this, many organizations and governments have developed and implemented early warning systems (EWS), which are structured frameworks or tools designed to identify emerging threats before they escalate (Papadopoulos, Stavroulias, & Sager, 2012).

EWS are utilized in a wide range of sectors, some of these include public health (to detect disease outbreaks) (Alahmari et al., 2024), environmental management (to forecast natural disasters such as floods or earthquakes) (Islam et al., 2025), cybersecurity (to identify data breaches or hacking attempts) (Apel et al., 2010), and in government policy. For instance, governments deploy EWS to monitor food security risks, manage disaster response, and assess financial vulnerabilities (UN Office for Disaster Risk Reduction, 2022; Food and Agriculture Organization, 2019). However, this thesis focuses specifically on EWS in the finance sector, as financial crises tend to leave behind widespread repercussions across economies and societies worldwide (Claessens & Kose, 2013). In finance, EWS are most often used by central banks, financial regulators, commercial banks, and international organizations such as the International Monetary Fund (IMF) and World Bank. Except for commercial banks, all of these are responsible for monitoring the stability of financial systems (Papadopoulos et al., 2012). These organizations rely on EWS in order to provide timely alerts, enabling governments and financial institutions to take action, such as adjusting regulations or providing liquidity, before a problem escalates into a full-blown crisis.

Traditional EWS in finance generally operate by continuously monitoring a selected set of macro-financial indicators, measurable variables that are known from experience to be linked with rising risk (Borio & Lowe, 2002). Typical indicators include the ratio of credit to gross domestic product (GDP), asset prices (such as housing prices or stock market indices), interest rates, and various measures of market liquidity (Borio & Lowe, 2002; Holopainen & Sarlin, 2017). EWS typically make use of statistical methods, which include such as regression analysis (a technique for estimating relationships between variables) or threshold-based rules (which issue a signal when an indicator crosses a predetermined value). The primary objective of applying these statistical methods is to identify predictive patterns, that is, recurring relationships or sequences in the data that reliably indicate an elevated risk or the onset of a financial crisis (Holopainen & Sarlin, 2017). For example, a warning might be triggered if the credit-to-GDP gap (the difference between the current credit-to-GDP ratio and its long-term trend) exceeds a certain level, or if several indicators jointly surpass pre-set thresholds. The goal is to convert complex, high-volume economic data into clear, actionable alerts that enable policymakers to intervene before a crisis develops. As financial systems have grown in complexity and size, these EWS must now process large amounts of data, sometimes including hundreds of time series and millions of observations, gathered from many countries and sectors (Bahoo et al., 2024).

Despite their proven effectiveness in some cases (Borio & Lowe, 2002), traditional EWS models often struggle to keep up with the growing complexity of global finance. One of the main challenges is that these systems heavily rely on traditional economic indicators and straightforward statistical techniques, which may not capture the intricate and fast-changing patterns created by new financial products, rapid electronic trading, and the increasing interconnectedness of markets worldwide (Holopainen & Sarlin, 2017). These limitations make it difficult for existing EWS to recognize predictive patterns (Chohan et al., 2025).

Advances in artificial intelligence (AI) and machine learning (ML) provide effective new approaches for analyzing complex data environments, such as those found in modern finance. They have emerged as promising means to overcome some of these stated limitations. Researchers and practitioners are increasingly exploring AI techniques to improve predictive patterns and outputs of EWS in the financial sector (Chohan et al., 2025). Broadly, AI refers to computer systems designed to perform tasks that would normally need human intelligence, including recognizing patterns, making decisions, or adapting to new information (Russell & Norvig, 2021). ML, a major subfield of AI, focuses on statistical algorithms and models which learn from data and improve their performance over time without the need of being explicitly programmed for each task (Mashrur, Luo, Zaidi, & Robles-Kelly, 2020). But AI itself also has several different types: “narrow AI” is specialized for a particular function (such as image recognition or translation); “general AI,” still largely theoretical, would match or surpass human cognitive abilities across multiple domains (Russell & Norvig, 2021); and “generative AI” can create new content, in the form of text or images, based on patterns it has learned (Feuerriegel, Hartmann, Janiesch, & Zschech, 2024).

In everyday life, most people interact with AI through digital assistants (like ChatGPT[1], Siri[2], or Alexa[3]), recommendation systems on streaming platforms (such as Netflix[4] or YouTube[5]), language translation tools, or image enhancement in smartphones. These consumer-facing AI systems are often designed for convenience and entertainment, utilizing pattern matching and data-driven predictions on a large scale (Malodia et al., 2021; Zhang et al., 2021; Mohamed et al., 2024; Pal et al., 2025). In contrast, the AI and ML models deployed in financial EWS are highly specialized: they are engineered to sift through millions of financial data points from multiple sources, detect subtle statistical anomalies, and flag complex combinations of variables that often precede periods of instability or crisis (Bahoo et al., 2024). So, rather than focusing on user personalization or content creation, these systems employ advanced predictive algorithms, such as ensemble learning (which combines the predictions of multiple models to improve accuracy), neural networks (human brain inspired computational models which can detect complex data patterns), or anomaly detection (methods for identifying unusual or outlier behavior in financial indicators) (Bahoo et al., 2024; Mashrur et al., 2020; Chohan et al., 2025). The goal is not only to find patterns but to generate reliable and timely signals for risk management in a highly dynamic and

[1] Chat.com
[2] The voice assistant of Apple
[3] The voice assistant of Amazon
[4] Netflix.com
[5] Youtube.com

interconnected financial environment (Bahoo et al., 2024; Chohan et al., 2025).

Integrating advanced AI and ML into EWS holds theoretical promise, studies show that AI-based models can uncover complex patterns and outperform traditional statistical methods in predicting financial risks: this improved accuracy and timeliness suggest that AI-enhanced EWS could substantially mitigate risks and guide proactive interventions (Edwards, Collins, Stewart, & Song, 2025). However, despite all of these capabilities, real-world adoption of AI/ML in financial EWS remains limited. Researchers and industry observers note a clear gap between the performance demonstrated in studies and the cautious implementation in practice. Financial institutions have been hesitant to widely deploy opaque AI models for critical risk monitoring, citing significant challenges in transparency, explainability, and regulatory compliance (Vuković, Dekpo-Adza, & Matović, 2025; Crisanto, Leuterio, Prenio, & Yong, 2024).

This thesis focuses on the finance sector because the consequences of financial crises, such as banking failures, widespread unemployment, increased public debt, and more, are often immediate, global, and substantial disruptive, making the ability to identify and mitigate such risks especially critical (Gorton, 2012). The financial sector produces and relies on vast amounts of high-frequency, high-dimensional data, which present unique opportunities for AI and ML to enhance the detection of predictive patterns and the generation of timely, actionable outputs in EWS (Bahoo et al., 2024). By going through a systematic analysis on how AI and ML methods can enhance traditional EWS frameworks, this research aims to clarify the extent to which these technologies can uncover subtle, complex relationships in financial data that reliably forecast periods of heightened risk. Specifically, this study examines whether integrating AI with EWS yields more accurate, timely, and interpretable signals for financial risk management. To achieve this, the thesis combines a systematic review of recent academic studies with original survey data from financial sector practitioners, thereby evaluating both the technical advances and the real-world adoption of AI-augmented EWS. The findings provide practical and methodological insights into how AI can strengthen the predictive power and utility of EWS in finance, thereby supporting more proactive risk management and enhancing financial system stability (Bahoo et al., 2024; Chohan et al., 2025; Vuković et al., 2025).

Thus, this thesis´ research question is:

"How can artificial intelligence enhance the predictive patterns and outputs of early warning systems in the finance sector?"

The remainder of this thesis is organized as follows. Chapter 2 explains the methodology employed, detailing the literature review process and the methods of building and sharing a survey. Continuing with Chapter 3, which presents and interprets the main findings, starting with results from the SLR, followed by a summary of relevant regulations for EWS, and then an analysis of the survey responses. The conclusion in which all key findings are summarized, the practical implications for managers, the discussion of limitations of this study, and finally, the areas where further research could be valuable, are all presented in Chapter 4.

2. METHODOLOGY

This chapter outlines the methodological approach employed to address the research question. In order to have a robust and comprehensive analysis ensured, this study employs a mixed-methods strategy that combines a systematic literature review (SLR) with an expert survey. The SLR was selected to provide a transparent and reproducible synthesis of recent academic advances comparing traditional and AI-augmented EWS in finance. To complement the literature findings and capture current industry perspectives, an anonymous survey was conducted among practitioners and experts in financial risk management. Combining these two methods integrates empirical evidence from published research with practical insights from professionals in this thesis. This will produce findings that are both academically grounded and relevant to policy and practice.

2.1 Systematic Literature Review

The primary method for gathering information in this study was a SLR, selected for its ability to ensure transparency, reproducibility, and comprehensiveness when synthesizing evidence in a rapidly developing research area (Tranfield, Denyer, & Smart, 2003; Moher et al., 2009). Literature was identified by constructing detailed search strings and applying them across several academic databases, including Scopus[6], Web of Science[7], Google Scholar[8], Springer Nature[9], ScienceDirect[10], and ResearchGate[11]. These platforms were chosen to maximize coverage of peer-reviewed articles, working papers, and conference proceedings relevant to AI, ML, and EWS in the financial sector.

To ensure that no major concepts or synonyms were overlooked, a wide range of keywords and "Boolean operators" was used, reflecting the diversity of terminology in the field. Boolean operators are words such as AND, OR, and NOT and are used to combine search terms, enabling researchers to refine or broaden the scope of their searches as appropriate for systematic reviews (Booth, Sutton, & Papaioannou, 2016). Key terms included "artificial intelligence" (AI), "early warning systems" (EWS), "machine learning" (ML), "finance," "risk,", "crisis", "predictive", "computing", "regulation", "and "output." The use of multiple, varied search strings (e.g., "artificial AND intelligence AND EWS AND finance", "machine AND learning AND predictive AND EWS") was necessary to capture the breadth of research, as terminology and emphasis can vary significantly between disciplines, journals, and over time (Booth, Sutton, & Papaioannou, 2016). For instance, some articles use the terms "artificial intelligence" or "machine learning.". In contrast, others use their acronyms "AI" or "ML" as standalone terms, and then other articles refer to specific techniques or applications in finance or economic modeling. The search strategy was thus intentionally broad, in line with best practices for systematic reviews, to ensure that relevant studies, regardless of slight differences in vocabulary or scope, were not missed (Mashrur et al., 2020).

The specific search strings included:

1. "artificial AND intelligence AND output AND finance"
2. "artificial AND intelligence AND EWS AND finance"
3. "artificial AND intelligence AND finance"

[6] https://www.scopus.com/search/form.uri?display=basic#basic
[7] https://www.webofscience.com/wos/woscc/basic-search
[8] https://scholar.google.com
[9] https://www.springernature.com/gp
[10] https://www.sciencedirect.com
[11] https://www.researchgate.net

4. “artificial AND intelligence AND economic”
5. “artificial AND intelligence AND computing AND EWS”
6. “predictive AND artificial AND intelligence AND finance”
7. “artificial AND intelligence AND early AND warning AND systems AND finance”
8. “artificial AND intelligence AND computing AND early AND warning AND systems”
9. “machine AND learning AND finance AND EWS”
10. “machine AND learning AND predictive AND EWS”

After collecting search results, all titles and abstracts were initially reviewed for relevance to the research question. Studies were included if they (1) focused on EWS in the financial sector, (2) presented or compared the application of predictive AI/ML techniques (e.g., neural networks, deep learning, ensemble learning, or hybrid models) to traditional econometric or statistical approaches, (3) presented empirical results using quantitative performance measures such as predictive accuracy, area under the curve (AUC; a measure of a model’s ability to distinguish between events such as crisis and non-crisis), lead time (the amount of advance warning provided before a crisis occurs), or error rates (the frequency of incorrect predictions, such as false positives and false negatives) were published in peer-reviewed venues in 2018 or later (Booth et al., 2016; Mashrur et al., 2020). Foundational works prior to 2018 were included only if they were widely cited or important for methodological context.

Papers were excluded if they (1) did not address the finance sector, (2) lacked a focus on EWS or comparable predictive models, (3) did not report sufficient empirical detail, or (4) were not available in English or could not be reliably translated (Moher, Liberati, Tetzlaff, Altman, & The PRISMA Group, 2009). Additional criteria that led to an exclusion were if the paper was an editorial, literature review without original analysis, non-peer-reviewed source, and conference abstract without full results. These inclusion and exclusion criteria ensured the review remained focused, high-quality, and directly relevant to the research question.

Data extraction concentrated solely on “usable” information, defined as data directly addressing the research question, such as model input variables, algorithm types, evaluation metrics, and reported outcomes. This approach minimized bias and improved the consistency and clarity of the synthesis (Tranfield et al., 2003; Booth et al., 2016). Language barriers were addressed using robust translation tools available for academic research (Hartley, 2014).

2.2 Survey Design and Administration

The survey was the secondary method of data collection and had the primary objective to validate key findings from the SLR. These should firstly be validated empirically and, additionally, uncover new insights from practitioners regarding the adoption and effectiveness of AI-augmented EWS in the finance sector. Surveys are widely recognized as an effective tool in management and finance research for capturing expert perceptions, benchmarking practice against theory, and supplementing literature-based findings with up-to-date, context-specific data (Groves et al., 2009; Saunders, Lewis, & Thornhill, 2019).

The survey was designed in Google Forms [12] to ensure easy access and, therefore, maximize the potential response rate (Fan & Yan, 2010). To further promote higher participation and reduce the percentage of respondents quitting, the questionnaire is intentionally brief (Deutskens et al., 2004). It contains 16 questions split into thirteen closed- and three open-ended ones (see Table 1). Another reason for this was to achieve a mix of quantitative data (such as multiple-choice questions for descriptive statistics and cross-tabulations) and qualitative feedback (such as free-text fields for nuanced opinions and practical examples), in line with best practices for survey design in organizational research (Bryman, 2016). The survey was fully anonymous to protect participants’ privacy and encourage candor. A pilot test of the survey was conducted with four fellow International Business Administration (IBA) students who remained anonymous throughout the process. Their feedback led to some adjustments in the wording of questions and the total length of the survey to ensure clarity, relevance, and overall usability before the survey was distributed. A standard step to increase the reliability and validity of survey instruments (Presser et al., 2004).

The survey was distributed by email to a diverse range of organizations, including central banks, regulatory authorities, commercial banks, financial technology (FinTech) firms, risk consultancies, rating agencies, and academic research groups. The selection of recipients was guided by the need to include professionals with direct or indirect experience in EWS or AI-driven financial risk monitoring. The intended respondent groups comprised:

- Staff at central banks or supervisors who interpret and act upon EWS outputs
- AI or data science specialists working in banks, FinTechs, or rating agencies who develop or maintain predictive models
- Risk-management professionals in financial firms who use EWS alerts for operational decision-making
- Consultants and technology vendors involved in the implementation of EWS/AI systems for clients
- Researchers based in universities or think tanks who analyze or publish on financial risk models

3. RESULTS AND DISCUSSION

This chapter presents and interprets the empirical findings from both the SLR and the survey. This was done to provide an integrated answer to the research question: *“How can artificial intelligence enhance the predictive patterns and outputs of early warning systems in the finance sector?”* The organization of this chapter is designed to support both transparency and coherence in the presentation of the results and their practical significance.

Section 3.1 synthesizes the principal findings from the SLR, including the historical development of EWS research and the adoption and comparative effectiveness of AI and ML techniques. Each subsection includes discussions and interpretations of the analyzed results, where appropriate, to highlight the implications of these findings for EWS design and financial risk management.

Section 3.2 provides an overview of relevant regulations for EWS and supervisory frameworks. This further outlines how

[12] https://docs.google.com/forms/u/0/

evolving guidelines influence the development, implementation, and governance of AI-enabled EWS in the financial sector.

Section 3.3 presents the survey results in an integrated manner, where each major theme is first introduced with a plain, descriptive summary of the relevant survey findings, such as respondent profiles, institutional use of EWS and AI, and perceptions of current approaches. Following this, an interpretation is provided that directly links the survey responses to the main findings from the SLR. Even with a very small sample size, this method makes sure that every result is clearly presented and thoughtfully placed into context, so it can be properly considered relevant for the broader field. Practical recommendations, limitations and suggestions for future research are summarized at the end.

3.1 Systematic Literature Review

The following review is structured in three major parts. First, an overview of the traditional EWS models is done. This is achieved by defining and explaining the most common models that are currently in use. In addition to that, their known limitations in predictive performance will be discussed. Secondly, contemporary AI techniques, such as ML algorithms, deep neural networks (multi-layered algorithms that can model complex, nonlinear relationships in data), and natural language processing (NLP; algorithms that translate human language to computers)-based methods will be explained, and how these have been applied to enhance financial prediction. Finally, findings on how AI specifically improves EWS predictive outputs are synthesized, considering evidence of improved model performance and timeliness, while also addressing challenges related to model interpretability, data integration, and compliance with regulatory expectations.

3.1.1 Traditional financial EWS

In practice, classical EWS implementations have taken two primary forms: *signal-based* approaches and *statistical classification* models. In the signal approach, pioneered by *Kaminsky* and *Reinhart* in the 1990s, a set of economic or financial indicators is continuously tracked; if an indicator crosses a predefined threshold (i.e. emits a "signal"), it indicates elevated risk of a crisis within some forthcoming horizon (Namaki et al., 2023). By monitoring multiple indicators (e.g., credit growth, foreign reserves, and exchange rate deviations), policymakers compile composite warning indices based on the frequency and quality of signals (Namaki et al., 2023). The signal method is intuitive but requires careful calibration of thresholds to balance false alarms and missed crises. The second major class of models involves *multivariate statistical* models, particularly *binary classification* techniques such as logit or probit regression. Starting with Martin's (1977) early work on bank failure prediction using logit, these models estimate the probability of a crisis (the binary outcome) as a function of explanatory variables such as macroeconomic indicators (Purnell et al., 2024; Namaki et al., 2023). For example, a logistic regression EWS might use variables like GDP growth, inflation, interest rates, or credit-to-GDP gaps to output the estimated likelihood of a banking crisis in a given quarter. Such models were widely adopted in the 1990s and 2000s for forecasting currency crises and banking crises (Namaki et al., 2023). They improved on the signal approach by considering multiple factors jointly and providing explicit probability outputs for risk levels. Variants and extensions include multinomial logit models to differentiate crisis severity, as well as panel regressions with country-fixed effects to capture heterogeneity (Namaki et al., 2023). Together, the signal approach and logit/probit models (often supplemented by expert judgment) formed the backbone of traditional EWS used by institutions like the IMF, central banks, and commercial banks.

3.1.2 Limitations in Predictive Capabilities

While classical EWS frameworks provided valuable insights, researchers have long noted several limitations that constrain their predictive performance. First, many traditional models assume linear and static relationships between indicators and crisis outcomes. In a simple logit model, for example, the effect of each predictor is linear and time-invariant (aside from some lags) (Holopainen & Sarlin, 2017). In reality, financial systems exhibit nonlinear dynamics - indicator thresholds for crisis may not be fixed, and combinations of factors can interact in complex ways. Such nonlinear or time-varying relationships are hard to capture with static regression coefficients or single-threshold rules (Purnell et al., 2024). A related issue is the "*one-size-fits-all*" variable selection: classical EWS require experts to choose a set of indicators a priori based on economic theory or historical correlations. This introduces the risk of omitting important predictors or including irrelevant ones. Because the pool of potential indicators is large, focusing on a fixed subset can leave the model blind to emerging risk factors.

Traditional EWS inevitably present researchers with two limitations. One of these is that the target and explanatory variables or financial signals must be selected a priori from a large set of economic variables. Second, these methods have difficulty identifying and representing nonlinear, time-varying, and multidimensional relationships" (Purnell et al., 2024). These constraints can lead to modest predictive power. For instance, threshold-based models face a trade-off between false alarms and missed crises - a low threshold yields frequent warnings (few missed crises but many false alarms), whereas a high threshold does the opposite (Huynh & Uebelmesser, 2024). It is challenging to tune such systems to be both timely and accurate. Indeed, many early EWS suffered from either over-predicting crises that never occurred or under-predicting events that did occur, undermining user confidence (Holopainen & Sarlin, 2017).

Empirical evaluations have found that out-of-sample performance of traditional EWS is often mediocre, with relatively low signal-to-noise ratios (high "noise" from false signals) (Barthélémy, Gautier, & Rondeau, 2024). Furthermore, classic models often use low-frequency data (such as quarterly or annual), which may not capture rapidly evolving market conditions, thus limiting timeliness. Another limitation involves lack of integration of diverse data: older EWS were typically based only on structured numerical data (e.g. macroeconomic time series), ignoring unstructured information such as news, social media, or network connections. Finally, the interpretability of traditional EWS is generally high (a plus), policymakers like simple threshold rules or a handful of risk ratios, but this simplicity might come at the cost of incomplete risk capture

3.1.3 Shift Toward AI and ML

The past decade has witnessed a substantial shift in EWS research and practice toward using AI and ML methods. A recent bibliometric review highlights a "shift from traditional statistical methods to advanced ML and AI techniques", with methods like neural networks, random forests, and gradient-boosted trees becoming increasingly pivotal (Chohan et al., 2025). In other words, analysts are training data-driven ML models on large financial datasets to discover complex patterns indicative of distress instead of relying solely on pre-set econometric models. The appeal of AI/ML lies in their ability to automatically detect nonlinear relationships, interactions, and hidden structures in data that human-designed indicators or linear models might miss.

For example, decision-tree based algorithms (like random forests and XGBoost) can handle high-dimensional data and capture interaction effects by recursively partitioning the data space (Purnell et al., 2024). Similarly, support vector machines and kernel methods can model nonlinear boundaries between "crisis" and "non-crisis" states. Researchers have applied such methods across numerous financial prediction tasks. Liu et al. (2022) demonstrate the use of ensemble ML models (random forests and gradient-boosted trees) to improve prediction of financial crises, finding that these approaches better capture nonlinear patterns and outperform traditional probit/logit models (Purnell et al., 2024). Notably, Liu and colleagues also incorporate Shapley value-based techniques to preserve interpretability, using these values to explore the causal relationships between macroeconomic variables and crises (Purnell et al., 2024). This indicates an awareness of the need to make AI models explainable even as they boost accuracy. In general, supervised ML algorithms, including logistic regression with regularization, k-nearest neighbors, support vector machines, decision trees, ensembles, and Bayesian classifiers, have all been tested as EWS predictors in recent literature (often in horse-race comparisons) (Holopainen & Sarlin, 2017). Results tend to show ML models equaling or surpassing classical models in predictive performance, especially when the financial system under study is complex or when using a rich feature set (Purnell et al., 2024).

3.1.4 Deep Learning and Neural Networks

Within AI, deep learning has gained prominence in predictive performance due to its ability to model highly nonlinear and complex functions, resulting in improved predictive performance. Deep neural networks, which consist of multiple layers of interconnected neurons, can approximate complex mappings from inputs (financial indicators or even raw data) to outputs (risk level). Early applications of neural networks to financial EWS appeared in the 2000s, but recent advances in network architectures and training techniques have significantly improved their efficacy. A key advantage of deep learning is its capacity to handle sequential and unstructured data. For instance, recurrent neural networks (RNNs) and their modern variants, LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) networks, are specifically designed to capture temporal dependencies (Barthélémy et al., 2024; Mashrur et al., 2020). An EWS for currency crises using LSTM and GRU networks, noting that these recurrent models "allow for taking into account nonlinear interactions between variables and the influence of past data in a dynamic form" (Barthélémy et al., 2024). Such models, originally developed for natural language processing tasks, have proven effective for financial time series as well (Hochreiter & Schmidhuber, 1997; Barthélémy et al., 2024). By training on historical time series from dozens of countries, the LSTM-based system learns patterns like how certain indicator trajectories (e.g. rapid reserve losses over consecutive months) can foreshadow a crisis (Barthélémy et al., 2024). Feed-forward deep networks (multi-layer perceptrons) have also been applied to examples of failures of EWS, such as bank failure prediction and corporate distress, often achieving higher accuracy than logistic regression by uncovering nonlinear combinations of financial ratios (Zhang, Zhu, & Hua, 2025). Moreover, convolutional neural networks (CNNs) have seen niche use, for example, in modeling market price movements by treating time series as "images" or in extracting features from financial graphs. A notable trend is the integration of deep learning with other techniques: some studies use hybrid models (e.g. combining wavelet transforms or decomposition methods with deep networks) to pre-process financial data and improve signal extraction (Purnell et al., 2024). Another innovation is the use of attention mechanisms, which allow models to focus on the most relevant time steps or features when making predictions. These advanced architectures (attention-based RNNs, Transformers) can improve prediction accuracy by dynamically weighting the importance of different indicators over time (Chohan et al., 2025). Overall, deep learning provides a powerful toolkit for EWS, especially as the quantity and complexity of financial data grow. However, neural networks are generally black box in nature, a point explained in the section on challenges.

3.1.5 Natural Language Processing (NLP) and Alternative Data

A significant enhancement to EWS enabled by AI is the incorporation of textual and other unstructured data as predictive signals. Traditional EWS largely relied on numerical metrics, but AI allows to quantify qualitative information (news, narratives, sentiments) that can presage financial risks. Natural language processing techniques, particularly those leveraging ML, have been proposed to gauge market sentiment and other risk-related insights from news articles, social media, financial disclosures, and even search trends. For example, a news sentiment index using an NLP model (FinBERT, a domain-tuned language model) was developed to analyze the tone of economic news (Stander, 2024). The study finds that this news-based sentiment index spikes before increases in systemic risk and can serve as an early warning signal of rising credit risk in the banking system (Stander, 2024). This is a clear illustration of AI enhancing an EWS. By processing textual narratives that would be infeasible to include in traditional models, the AI-driven index provided advance warning that complements numerical indicators. Similarly, researchers have used social media data (like Twitter[13] feeds) to detect shifts in investor sentiment or panic that might foreshadow market turmoil (Stander, 2024). AI models can perform sentiment analysis at scale, turning millions of posts or news headlines into sentiment scores or risk flags in real time. Another application is using NLP to analyze corporate reports or news for credit risk, for instance, unusual frequency of negative words in a firm's filings might signal financial stress, thereby augmenting a corporate default EWS (Zhang, Z. et al., 2025). Beyond text, AI can handle other alternative data such as network data and high-frequency market data. Network analytics can be combined with ML so that interconnectedness (e.g. interbank exposures) is factored into early warnings (Purnell et al., 2024). High-frequency trading data can be mined with deep learning to spot anomalies that precede market crashes (e.g. by using sequence models on order book data). In sum, it is now possible for AI techniques to greatly expand the feature space for EWS by enabling the use of unstructured, high-volume data sources that were previously out of reach. Both the accuracy and the timeliness of warnings can be improved, as the models can pick up subtle signals (like shifts in sentiment or liquidity) earlier than traditional indicators might reflect.

3.1.6 AI for Improved Timeliness and Adaptability

ML systems can process continuous streams of data and update risk assessments as new information becomes available, which makes them stand out in real-time analysis and adaptability (Shen, 2024). This approach differs significantly from many traditional EWS that still rely on set time intervals for updates. Some modern risk tools do not rely on these set intervals. They are able to track live market data and pick up patterns of stress as they develop. This new ability leads to a more proactive response to risk (Shen, 2024). The ability to learn and adapt to new data is necessary in a volatile financial environment. AI models,

[13] X.com

especially those online or retrained frequently, can adjust to structural changes or new risk factors without requiring a manual model redesign: AI "continuously learns and adapts to new data, improving their predictive accuracy over time", which allows firms to respond more effectively to changing conditions (Shen, 2024). This adaptability means an AI-based EWS might automatically recalibrate itself as it observes new crisis events or shifting relationships, something very difficult for static regression models.

Additionally, AI allows scenario simulation and stress testing in a more flexible way : for instance, one can use an ML model to simulate what-if scenarios (by perturbing inputs) to see how risk predictions change, potentially revealing nonlinear sensitivities (Shen, 2024). When viewed from an operation standpoint, AI is also able to trigger automated decisions or alerts when certain risk thresholds are breached, which streamlines the whole early response process (Shen, 2024). Overall, the infusion of AI techniques into EWS has brought clear benefits: richer data inputs, more complex pattern recognition, and dynamic learning capabilities (Barthélémy et al., 2024; (Mashrur et al., 2020). How these AI-driven enhancements translate into better predictive performance and the practical considerations that accompany these improvements will be synthesized in the next chapter.

3.1.7 Improved Predictive Performance

A central finding across recent studies is that AI-enhanced EWS generally outperform traditional models in predicting financial risks. The inclusion of nonlinearity, interactions, and big data often yields higher accuracy, earlier detection, or both. Empirically, ML models have shown higher true positive rates (crisis hits) and/or lower false alarm rates than their statistical counterparts (Barthélémy et al., 2024; Holopainen & Sarlin, 2017; Purnell et al., 2024). For example, in a comprehensive comparison, studies found that advanced ML methods like neural networks and ensemble learners significantly outperformed logistic regression in out-of-sample crisis prediction, especially when combined through ensemble averaging (Holopainen & Sarlin, 2017). More recently, it was demonstrated that a deep learning EWS for currency crises would have correctly issued warnings for 91% of actual crises within a two-year window (Barthélémy et al., 2024). Not only is the hit rate high, but the false alarm rate was substantially lower, the LSTM model's warnings were false only 14% of the time, compared to 23% for a benchmark logistic regression (Barthélémy et al., 2024). This indicates a more efficient tradeoff between sensitivity and specificity: the AI system was better at distinguishing true signals from noise, which is echoed by other studies: Samitas et al. (2022) applied ML to a network-based systemic risk EWS and achieved a 98.8% predictive effectiveness in identifying contagion-driven crises. Such a result approaches a very high classification (though possibly hinting at overfitting, as the authors caution) (Purnell et al., 2024). The clear message is that AI models can capture early-warning patterns that eluded simpler models, for instance, complex combinations of macro indicators, market trends, and even textual sentiment that collectively indicate rising risk. By leveraging many inputs and flexible functional forms, AI systems often detect crises earlier (providing a longer lead time) or with fewer false signals. It is worth noting that performance gains are context-dependent: in relatively stable, linear scenarios, traditional models may perform adequately and be preferable for their simplicity. But in complex scenarios, say, predicting systemic banking crises that involve network effects and nonlinear feedback, AI models have shown markedly better results (Purnell et al., 2024; Holopainen & Sarlin, 2017; Barthélémy et al., 2024). The so-called ensemble approaches (combining multiple models) have proven themselves as very powerful. By aggregating the forecasts of different AI models, one can reduce idiosyncratic errors and achieve robust predictions. For instance, an ensemble of decision trees, SVMs, and neural networks can collectively cover various facets of the data, delivering more stable warning signals (Purnell et al., 2024). AI techniques enhance the predictive outputs of EWS in terms of accuracy, lead time, and reliability of the warnings as suggested by the presented evidence. Thereby potentially enabling stakeholders to take preemptive measures more effectively.

3.1.8 Integration of Diverse Data (Breadth of Signals)

AI-enhanced EWS are also superior in their breadth of vision, i.e. the ability to integrate a wide array of data sources into the risk assessment (Shen, 2024). This comprehensive perspective improves predictive power since financial crises often have multiple causes and early signs that manifest across different domains. An AI system can simultaneously consider macroeconomic trends, firm-level metrics, market indicators, and sentiment/behavioral data, whereas a traditional system might be limited to a handful of macro variables. For example, a modern credit risk EWS might combine a borrower's financial ratios with their industry news sentiment and even their social media reputation. AI algorithms can handle this heterogeneity. As described, "AI algorithms analyze a wide range of data sources, such as social media activity and transaction history, to identify patterns and correlations that traditional methods might overlook," leading to more accurate risk predictions (Shen, 2024). In practice, this means an AI-driven EWS for banks could pick up on early signs of trouble from alternative data, say, a surge in negative news about a bank's liquidity or unusually high search engine queries about the bank (a digital "run" signal), well before balance-sheet indicators deteriorate. The ability to incorporate real-time market data and unstructured data also improves the timeliness of warnings. Traditional EWS relying on quarterly data might only flash warning after a quarter's end, but an AI model ingesting daily market volatility or weekly news sentiment can update risk assessments almost continuously (Shen, 2024). This real-time monitoring can catch abrupt shifts (like sudden market sell-offs or policy announcements) that static models would miss. Moreover, AI can capture cross-market linkages: for instance, an AI EWS could learn that a certain pattern in U.S. yield curve and European bank credit default swaps, combined with a spike in Google searches for "bank insolvency," is an ominous constellation for emerging-market banks. Such complex cross-indicator signals would be beyond a manual threshold approach. By combining macroeconomic trends, firm-level signals, and alternative sources like news sentiment, AI-enhanced EWS provide a broader, more integrated risk perspective than traditional models. This approach not only helps to detect early signs of instability that might otherwise go unnoticed but also supports the delivery of clearer, more actionable alerts. Recent studies emphasize that including both conventional indicators and less-structured data is key to raising predictive accuracy (Namaki et al., 2023). With these advances, EWS outputs can be made more informative and transparent for decision-makers, for example, by using risk dashboards that highlight the main drivers behind each alert (Purnell et al., 2024; Barthélémy et al., 2024).

3.1.9 Improved Interpretability Solutions

Paradoxically, one challenge of AI models, their complexity and opaqueness, has led to new techniques that enhance interpretability alongside predictive performance. Traditional EWS were favored by policymakers in part because of their transparency (it is easy to explain "credit growth > x% triggers a warning"). AI models, especially deep learning, are often criticized as “black boxes” that lack clear reasoning, which can be problematic for trust, compliance, and decision-making. Recognizing this, researchers are actively integrating explainable AI methods (xAI; AI methods that make model decisions transparent and understandable to humans) into EWS frameworks (Purnell et al., 2024; Crisanto et al., 2024; Zöller et al., 2024). One common approach is to use post-hoc explanation tools like SHAP (Shapley Additive Explanations) (Lundberg & Lee, 2017) or LIME (Local Interpretable Model-Agnostic Explanations) (Ribeiro et al., 2016) to quantify how each input variable influences the model’s predictions. For example, after an ML model predicts a high probability of crisis, a SHAP analysis might reveal that surging private debt and falling bank stock prices were the top contributors to that particular warning. This gives analysts a handle on why the model is warning, restoring some transparency. As noted, incorporated Shapley-value methods to explore causal relationships in their crisis prediction model, which helped interpret how GDP, interest rates, and other variables are linked to predicted crises (Purnell et al., 2024). Another strategy is the surrogate model (Molnar, 2022), where a complex ensemble or network model is used to identify the important predictors and relationships, but the final EWS output is generated by a simpler, interpretable model (like a linear regression) using those key features (Purnell et al., 2024). In the study, Purnell and colleagues first designed an ensemble of ML algorithms and a Shapley-based feature selection to find a small subset of 14 critical variables (out of an initial 3160) that signal network instability (Purnell et al., 2024). They then train an “explainable linear model” on those variables to produce the warnings, specifically because “economics and regulatory policy require explainable and easy-to-use models”, and pure ML models are insufficient on those fronts due to their black-box nature (Purnell et al., 2024). This approach retained high predictive power while improving interpretability and parsimony. The collapse of Silicon Valley Bank in 2023 was used as a case study, and the model successfully identified the instability trend leading up to the failure using that small set of features (Purnell et al., 2024). This kind of hybrid solution, AI for detection, human-interpretable model for communication, is a compelling way to enhance EWS outputs for practical use. It means policymakers get both an accurate warning and a clear explanation (e.g. “the model is warning because Metric A and Metric B have reached levels historically associated with crisis”). Thus, AI has spurred not only better predictions but also new methods to translate those predictions into actionable insights that stakeholders can understand and trust.

3.1.10 Discussing Practical Challenges: Transparency, Compliance, and Implementation

There still remain practical challenges to be solved in deploying these systems in the finance sector despite the documented benefits of AI-enhanced EWS. Transparency and governance of AI models are chief among them. Financial institutions operate in a heavily regulated environment, where models that drive important decisions (such as capital buffers or supervisory actions) may need to be auditable and justifiable to regulators. Black-box AI models can conflict with regulatory requirements for model risk management and accountability (Crisanto et al., 2024; Vuković et al., 2025; Zöller et al., 2024; Basel Committee on Banking Supervision, 2013). Regulators have increasingly signaled that the use of opaque AI will not excuse inadequate decisions. For example, recent guidance emphasizes that “black-box” logic is no defense for unintended biased outcomes in credit decisions (Patel, 2025). In the context of EWS, a model that issues false positives without an explainable basis could lead to either regulatory skepticism or misinformed actions. Compliance departments thus demand that AI EWS adhere to fair and transparent modeling practices, and that they do not rely on prohibited data (like certain personal data in credit models) or violate privacy laws. The industry response, as noted, has been the adoption of XAI techniques and simpler surrogate models to ensure interpretability and compliance. By building explainability in AI-driven EWS can satisfy the “why” question for each warning, which is necesssary for gaining management and regulatory buy-in (Purnell et al., 2024). Another challenge is data quality and infrastructure. AI models usually require large datasets and robust computing resources. Firms may need to invest in integrating data from different sources (market feeds, news APIs, etc.) in real time and ensure data integrity. Low quality data will lead to inadequate models, so data governance is as important as ever. Model overfitting is also a risk; a highly complex AI model might fit past crises well but then fail to predict a new type of crisis. The 98.8% accuracy example by Samitas et al. (2022) raises this concern, as such a performance might not generalize (Purnell et al., 2024). To mitigate this, rigorous validation, stress testing on different scenarios, and regular model updates are needed. In operational terms, AI EWS should complement, not fully replace, human judgment. Many institutions can implement them as a support tool for decision-making: the AI flags risks, and human analysts further investigate and decide on actions. This helps catch any model errors and adds a layer of expert oversight. Finally, there is the issue of adapting organizational processes, staff may need training to interpret AI model outputs, and workflows must accommodate potentially more frequent or earlier warnings. When an AI system issues an alert, institutions should have protocols to respond (e.g. perform a deeper risk review, increase monitoring of a particular exposure, etc.). In summary, financial institutions must address transparency and compliance through explainability features, (Purnell et al., 2024), maintain rigorous model risk management practices, and ensure that the improved predictive power translates into effective and prudent decision-making even though that AI greatly enhances EWS capabilities.

3.2 EWS Regulations

The regulatory environment for EWS is complex. The use of these systems in the financial sector is shaped by a range of international regulations and supervisory guidelines. Understanding these rules is important for explaining how EWS are put into practice and what standards institutions must follow. The Basel Committee on Banking Supervision (BCBS) establishes the foundation through standards such as the Basel III and IV Accords, which require robust risk identification and reporting systems to ensure capital adequacy and systemic resilience (Basel Committee on Banking Supervision, 2017). In particular, BCBS 239 sets out principles for effective risk data aggregation and reporting, obligating institutions to maintain high standards for data quality, model transparency, and traceability in all risk management tools, including EWS (Basel Committee on Banking Supervision, 2013).

At the European level, the European Banking Authority (EBA) further specifies requirements through regulatory technical standards and supervisory guidance. The EBA Guidelines on ICT and security risk management instruct financial institutions to ensure the security, reliability, and auditability of all information and communication technology, including EWS platforms (European Banking Authority, 2019).

The regulatory landscape is now increasingly focused on the impact of AI in financial risk management. The proposed EU Artificial Intelligence Act classifies AI systems used for credit scoring and risk assessment as “high-risk,” imposing further requirements related to transparency, data governance, and human involvement in decision-making processes (European

Commission, 2021). These requirements are especially relevant for AI-augmented EWS, which must demonstrate their ability to produce understandable outputs and support supervisory review (Zöller, Iurshina, & Röder, 2024).

In practice, these regulatory standards mean that any institution deploying EWS, especially those integrating AI, must ensure rigorous validation, comprehensive documentation, and regular model monitoring, while facilitating access for supervisory authorities (Basel Committee on Banking Supervision, 2013; European Commission, 2021; Zöller et al., 2024). The environment with the current regulations in place aims to find a balance between innovation in early-warning methodologies and the principles of financial stability, transparency, and accountability in risk management.

3.3 Survey Results

To complement the systematic literature review, an industry survey was administered with the goal of capturing professional perspectives on the current usage, limitations, and future outlook for AI in EWS for financial risk detection. The survey consisted of three main sections: (1) respondent background and experience, (2) EWS usage and institutional adoption, and (3) views on AI integration, perceived barriers, and anticipated trends. A total of three responses were received, all from individuals identifying as academic researchers with less than three years of experience in the financial sector. Due to the extremely limited sample size and also the lack of diversity in professional backgrounds, the findings from this survey should be considered exploratory and interpreted with caution, as they are not representative of the broader industry landscape. The following section presents the survey results, organized by section according to the survey's structure, starting with respondents' profiles and proceeding through institutional EWS adoption and professional perspectives on AI-enabled EWS.

3.3.1 Respondent Profile

The survey component of this study, intended to complement the findings of the SLR, yielded a very limited response rate, with only three participants completing the questionnaire. All respondents identified themselves as academic researchers with less than three years of professional experience in the financial sector. Notably, none were directly affiliated with financial institutions, regulatory bodies, or private-sector firms actively developing or deploying EWS or AI applications in operational financial risk management (see Figure 1 and 2). The specialized nature of the survey topic is reflected by the narrow pool of respondents. As such, the respondent profile in this case is characterized by early-career academics who, despite having theoretical knowledge of EWS and AI, may not possess direct, hands-on experience with the practical challenges of implementing AI-driven EWS in real-world financial settings. The academic and novice status of the respondents suggests that their insights are likely more aligned with scholarly perspectives and may lack the practical nuance that could be provided by more experienced industry professionals (Groves et al., 2009; Saunders et al., 2019). So, it is important to interpret the results as exploratory and illustrative ones rather than them being representative of broader industry practice or consensus.

3.3.2 EWS Usage and Institutional Adoption

None of the respondents indicated that their institution or they as individuals currently use an EWS to monitor financial risks, nor do they have plans to implement one. Two respondents, however, noted familiarity with EWS concepts (rated at level 4 out of 5), while one rated their familiarity as low (2 out of 5) (see Figure 3 and 4). This finding closely mirrors trends in the literature: while research on AI-driven EWS is expanding, the SLR shows that institutional adoption in real-world finance remains limited (Bahoo et al., 2024; Chohan et al., 2025). Barriers such as resistance to change, unclear regulations, and limited resources are often mentioned as reasons why EWS are not used more widely. The fact that none of the survey participants reported adopting EWS highlights again the ongoing gap between developments in research and what is actually used in practice.

3.3.3 Current Approaches and Model Use

Regarding the types of EWS approaches used, two respondents mentioned "Traditional statistical models (e.g., logit, probit, threshold)" but clarified that no formal system is in place. The third respondent selected "No system in place." When asked about the effectiveness of current EWS models for predicting financial distress, all three respondents gave a neutral score (3 on the scale), reflecting neither strong satisfaction nor dissatisfaction (see Figure 5 and 6). The SLR documents a similar trend: traditional statistical models (e.g., regression-based EWS) remain the norm where EWS are in place, and adoption of AI-enhanced models is mainly limited to pilot projects and academic research (Chohan et al., 2025; Bahoo et al., 2024). This lack of institutional use among survey respondents corroborates the SLR's finding that most financial firms have yet to operationalize the full potential of ML and DL in risk monitoring.

3.3.4 Limitations of Current EWS

When asked about the greatest limitation of current EWS frameworks, "Data quality and availability" was chosen by two respondents, while one cited "Lack of skilled personnel." This suggests that, among this sample, fundamental data and human capital constraints are perceived as primary obstacles to effective EWS (see figure 7). This criticism directly aligns with the literature. The SLR (Bahoo et al., 2024; Namaki et al., 2024) repeatedly highlights that established EWS models often fail to detect subtle or nonlinear risk patterns in complex financial environments.

3.3.5 AI and ML Adoption

Regarding the adoption of AI or ML in daily workflow, two respondents described their institution or personal use as being in the "Pilot phase." In contrast, one described it as "Somewhat integrated." None described full-scale or advanced integration of AI/ML technologies in the context of EWS (see Figure 8). This mirrors the findings in the SLR, which point to a pronounced academic shift toward ML, DL, and ensemble learning models (Bahoo et al., 2024; Song et al., 2025). However, the transition from academic exploration to operational use is slow, due to both technical and organizational hurdles. The literature confirms that most AI applications in EWS are still in experimental or pilot stages rather than integrated into day-to-day practice.

3.3.6 Perceptions of AI Potential

When asked how much AI/ML could enhance traditional EWS, one respondent answered "Moderately," while two chose "Significantly." For the most promising AI methods, two respondents pointed to "Neural Networks" and "LSTM (Long Short-Term Memory)," while one respondent declined to answer without more information about the available data. Graph Neural Networks (GNNs) were also mentioned by one respondent (see Figure 9 and 10). This optimism is well-supported by the SLR: It documents the superior predictive performance of ensemble and deep learning models in empirical studies (Bahoo et al., 2024; Song et al.,2025). However, their "black box" nature and the resulting difficulties in explanation and regulatory acceptance remain significant barriers.

3.3.7 Requirements and Risks

As for the most critical requirement for trustworthy AI in financial EWS, respondents gave different answers: “Robust validation of model accuracy,” “Data privacy & GDPR compliance,” and “Explainability & interpretability.” This diversity reflects the variety of concerns that remain central to AI adoption in financial risk monitoring. When asked whether the benefits of AI in EWS outweigh the potential risks (such as model opacity or bias), two respondents gave a neutral score (3), while one respondent was slightly more positive (4 on the scale) (see Figure 11 and 12). These points reinforce the SLR’s emphasis on practical challenges. Both the literature and survey responses highlight that predictive gains alone will not drive adoption; rather, interdisciplinary collaboration, regulatory engagement, and investment in human capital for interpretability reasons are required for trustworthy, sustainable implementation (Bahoo et al., 2024; Crisanto et al., 2024).

3.3.8 Qualitative Responses and Open Feedback

- Only one respondent provided an open comment regarding the future role of AI, suggesting “Automation and influence of opinions” in the next 3–5 years.
- One respondent stated that the single biggest improvement needed for current EWS frameworks is “Learnability.”
- For integrating AI more effectively, one suggestion was that “AI should be used to train EWS.”

4. CONCLUSION

This thesis set out to answer the research question: *“How can artificial intelligence enhance the predictive patterns and outputs of early warning systems in the finance sector?”*. To address this, the study combined a SLR of recent peer-reviewed research with a survey designed to capture professional perspectives. The synthesis of the presented sources provides a detailed and balanced understanding of both the current and emerging roles of AI in the evolution of financial EWS.

The findings from the literature review reveal that AI has driven a significant transformation in EWS within the finance sector. By incorporating ML, deep learning, and NLP, AI-enabled systems can identify complex risk patterns with greater accuracy and speed than traditional approaches. These advanced models integrate a a lot of data that ranges from macroeconomic indicators to granular market signals and text-based sentiment, offering a more holistic view that can reduce blind spots and improve the reliability of warnings. Recent empirical studies have shown that such models achieve higher predictive accuracy and a lower rate of false alarms, which in turn increases trust in early warning outputs (Barthélémy et al., 2024; Purnell et al., 2024). In addition to this, the introduction of explainable AI techniques allows for clearer interpretation of predictions, helping to ensure that the reasoning behind alerts is accessible to both technical and non-technical stakeholders (Purnell et al., 2024). This combination of improved performance and transparency is necessary for effective implementation. As a result, regulators and industry leaders have become more supportive of AI in risk management, provided that standards for governance and transparency are met. Looking ahead, further integration of AI into EWS is expected to include more real-time monitoring, expanded use of global interconnected data, and adaptive learning capabilities that respond to evolving financial risks. However, the fact that AI is not a simple solution for all challenges remains clear. But when it is deployed with the right thought in mind, it can offer considerable improvements in the predictive capacity and utility of EWS, which will contribute to a more resilient financial sector.

These findings are echoed in the results of the survey. Even though the small sample size and academic background of respondents means that the conclusions of the survey cannot be generalized, the perspectives collected through the survey reflect clear optimism about the potential of AI to improve EWS. Respondents highlighted benefits such as greater predictive accuracy. At the same time, concerns about model interpretability, regulatory requirements, and the need for skilled human capital to oversee AI remain visible. Their responses reinforce the literature’s main point: that successful integration of AI depends not only on technical advances, but also on rigorous model validation, open and clear communication, and strong links to domain expertise.

Summarizing the thesis, the presented evidence supports a clear conclusion. AI is able to meaningfully enhance the predictive patterns and actionable outputs of EWS in the finance sector. AI-based systems provide a more comprehensive, timely, and interpretable approach to financial risk detection. This directly supports earlier and more effective interventions by regulators and market participants alike. When both, the technology and regulatory standards continue to develop, it is likely that AI will become a standard part of risk management practice, helping to safeguard the stability of the financial system.

4.1 Managerial Implications

Summarizing the findings of this study, several practical implications are highlighted for managers and decision-makers in the financial sector that need to be considered when it comes to the implementation of AI-driven EWS:

Prioritize Transparency and Explainability:

Managers should ensure that AI-enabled EWS are transparent and easily interpretable by staff. Employing explainable AI techniques, such as SHAP, can help stakeholders understand how predictions and alerts are generated, which is necessary for building trust internally and meeting regulatory requirements (Crisanto et al., 2024; Purnell et al., 2024).

Invest in High-Quality Data Infrastructure:

To effectively leverage AI-driven EWS, managers need to focus on robust data infrastructure. This involves integrating diverse data types, including macroeconomic indicators, market data, and unstructured data like news sentiment, and maintaining high standards for data quality through consistent cleaning, validation, and governance practices (Barthélémy et al., 2024).

Encourage Cross-Functional Collaboration:

Technical and organizational challenges arise when it comes to the implementation of new systems, such as AI. That is why managers should make sure that data scientists, risk analysts, compliance officers, and business experts work together on a regular basis. By doing so, models that are technically robust, practically useful, and aligned with organizational goals and compliance standards can be implemented (Crisanto et al., 2024).

Stay Proactive with Regulatory Compliance:

Because regulations are changing, managers need to stay up to date and respond quickly to new supervisory requirements. Having clear processes for checking models, keeping records, and running regular audits helps organizations follow rules about transparency, fairness, and accountability (Crisanto et al., 2024).

Enhance Human Capital and Training:

Employees must be able to manage and work with new EWS as part of their daily responsibilities. That is why it is important for organizations to provide regular training and opportunities for further learning. These trainings would ensure that staff are able to respond to technical updates, understand regulatory requirements, and address new challenges as they arise. This ongoing investment in skills and knowledge helps organizations maintain strong risk management and adapt to changes in the wider financial environment.

Adopt a Gradual Implementation Approach:

Because advanced EWS can be complex, it makes sense for organizations to introduce new models in stages. Managers can start by testing these systems alongside existing processes, evaluate their results, and only expand their use once there is enough experience and confidence with the technology (Bahoo et al., 2024).

4.2 Limitations and Future Study Suggestions

While this study provides valuable insights into the role of AI in enhancing EWS for financial risk detection, two main limitations must be acknowledged. Following these, suggestions for future studies are discussed.

The major limitation was that the survey sample is extremely limited since it only consists of only three respondents and all of whom were academic researchers with less than three years of experience in the financial sector. This small and homogenous group restricts the representativeness and generalizability of the survey findings, which should therefore be interpreted as exploratory rather than definitive.

The second limitation was that this research did not include detailed case studies or direct examination of financial institutions currently using EWS based on AI. As a result, the study's conclusions about practical challenges, regulatory issues, and the effects of implementation rely on information from published research and survey responses, rather than from direct, real-world observation or experience within organizations.

To begin with the suggestions, future studies should mainly focus to build a strategy with which their survey(s) can reach much more respondents. The survey must not only reach more in numbers but also a broader and more diverse group of participants to receive greater insights into how EWS are used in practice. This larger and more varied sample would also help clarify what works, what needs improvement, and where EWS bring the most value.

Furthermore, there is a strong need for in-depth case studies and research that follows EWS implementations over time. Future studies must focus on how these systems perform within specific financial institutions or regulatory bodies, so, practical lessons about their effectiveness, the obstacles faced during integration, and what kinds of ongoing support help ensure long-term success can be revealed.

ACKNOWLEDGEMENTS

First of all, I would like to thank my two Supervisors, Dr. M.R. Machado and Dr.Ir. W.J.A. van Heeswijk for the continues support throughout the research process. A special thank you is addressed to my 1st Supervisor, Dr. M.R. Machado, for his guidance, feedback, and constant reliability. The fact that he was available all the time and often answered within minutes helped me a lot. Without him, I could have not completed this project. Furthermore, I want to thank the University of Twente for providing necessary materials and a work-environment to focus on the project. Finally, I am grateful for my family which patiently supported and encouraged me all along during this study.

REFERENCES

Romer, C. D. (1990). The Great Crash and the onset of the Great Depression. *The Quarterly Journal of Economics, 105*(3), 597–624. https://doi.org/10.2307/2937892

Shiller, R. J. (2000). *Irrational exuberance*. Princeton University Press.

Gorton, G. (2012). *Misunderstanding financial crises: Why we don't see them coming*. Oxford University Press.

International Monetary Fund. (2020, April). *World economic outlook: The Great Lockdown*. Retrieved June 20th, 2025, from https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/weo-april-2020

Holopainen, M., & Sarlin, P. (2017). Toward robust early-warning models: A horse race, ensembles and model uncertainty. *Quantitative Finance, 17*(12), 1933–1963. https://doi.org/10.2139/ssrn.2584343

Borio, C., & Lowe, P. (2002). *Asset prices, financial and monetary stability: Exploring the nexus* (BIS Working Paper No. 114). Bank for International Settlements. https://doi.org/10.2139/ssrn.846305

Papadopoulos, S., Stavroulias, P., & Sager, T. (2012). Systemic early warning systems for EU15 based on the 2008 crisis [Working paper]. Bank of Greece, Economic Analysis and Research Department - Special Studies Division. https://doi.org/10.2139/ssrn.4185896

Schmitt, M. (2022). Deep learning in business analytics: A clash of expectations and reality. Journal of Business Research, 151, 546–557. https://doi.org/10.48550/arXiv.2205.09337

Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in finance: A comprehensive review through bibliometric and content analysis. *SN Business & Economics, 4*(23), 1–46. https://doi.org/10.1007/s43546-023-00618-x

Chohan, M. A., Li, T., Ramakrishnan, S., & Sheraz, M. (2025). Artificial intelligence in financial risk early-warning systems: A bibliometric and thematic analysis of emerging trends and insights. *International Journal of Advanced Computer Science and Applications, 16*(1), 1335–1351. https://dx.doi.org/10.14569/IJACSA.2025.01601127

Shen, Q. (2024). AI-driven financial risk-management systems: Enhancing predictive capabilities and operational efficiency. Applied & Computational Engineering, 69(1), 141–146. https://doi.org/10.54254/2755-2721/69/20241494

Zöller, M.-A., Iurshina, A., & Röder, I. (2024). **Trustworthy generative AI for financial services.** In *Proceedings of the Symposium on Scaling AI Assessments (SAIA 2024)* (Article No. 2). Schloss Dagstuhl – Leibniz-Zentrum für Informatik. https://doi.org/10.4230/OASIcs.SAIA.2024.2

Namaki, A., Eyvazloo, R., & Ramtinnia, S. (2024). **A systematic review of early warning systems in finance.**

Basel Committee on Banking Supervision. (2013). Principles for effective risk data aggregation and risk reporting (BCBS 239). Bank for International Settlements. Retrieved June 20th , 2025, from https://www.bis.org/publ/bcbs239.pdf

Basel Committee on Banking Supervision. (2017). Basel III: Finalising post-crisis reforms. Bank for

International Settlements. Retrieved June 20th, 2025, from https://www.bis.org/bcbs/publ/d424.pdf

European Banking Authority. (2019). EBA Guidelines on ICT and security risk management. Retrieved June 20th, 2025, from https://www.eba.europa.eu/regulation-and-policy/internal-governance/guidelines-on-ict-and-security-risk-management

European Commission. (2021). Proposal for a regulation laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Retrieved June 20th, 2025, from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206

UN Office for Disaster Risk Reduction. (2022). Early Warning Systems. Retrieved June 20th, 2025, from https://www.undrr.org/terminology/early-warning-system

Mashrur, A., Luo, W., Zaidi, N. A., & Robles-Kelly, A. (2020). Machine Learning for Financial Risk Management: A Survey. IEEE Access, 8, 203203–203223. https://doi.org/10.1109/access.2020.3036322

Claessens, S., & Kose, M. A. (2013). Financial crises: Explanations, types, and implications (IMF Working Paper No. 13/28). International Monetary Fund. Retrieved June 20th, 2025, from https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Financial-Crises-Explanations-Types-and-Implications-40283

Food and Agriculture Organization. (2019). Early warning early action report on food security and agriculture. Retrieved June 20th , 2025, from https://openknowledge.fao.org/server/api/core/bitstreams/3bfee76c-88ac-4097-a001-134430c0b79a/content

Booth, A., Sutton, A., & Papaioannou, D. (2016). Systematic approaches to a successful literature review (2nd ed.). SAGE Publications. Retrieved June 20th, 2025, from https://www.researchgate.net/profile/Andrew-Booth-2/publication/235930866_Systematic_Approaches_to_a_Successful_Literature_Review/links/5da06c7f45851553ff8705fa/Systematic-Approaches-to-a-Successful-Literature-Review.pdf

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G., & The PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. PLoS Medicine, 6(7), e1000097. https://doi.org/10.1371/journal.pmed.1000097

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British Journal of Management, 14(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Russell, S., & Norvig, P. (2021). Artificial Intelligence: A Modern Approach (4th ed.). Pearson.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Coombs, C., Edwards, J., Misra, S., ... & Wade, M. R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Edwards, R., Collins, E., Stewart, A., & Song, M. (2025). AI-Driven Early Warning Systems for Financial Distress Prediction in SMEs. Retrieved June 20th, 2025, from https://www.researchgate.net/publication/392434031_AI-Driven_Early_Warning_Systems_for_Financial_Distress_Prediction_in_SMEs#:~:text=The%20%20AI,pe%20rformance%20compared%20%20to

Vuković, D. B., Dekpo-Adza, S., & Matović, S. (2025). AI integration in financial services: a systematic review of trends and regulatory challenges. Humanities and Social Sciences Communications, 12(1), Article 562 https://doi.org/10.1057/s41599-025-04850-8

Crisanto, J. C., Leuterio, C. B., Prenio, J., & Yong, J. (2024). Regulating AI in the financial sector: recent developments and main challenges. FSI Insights No. 63. Bank for International Settlements. Retrieved June 20th, 2025, from https://www.bis.org/fsi/publ/insights63.htm

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. Business & Information Systems Engineering, 66(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Zhang, Q., Lu, J., & Jin, Y. (2021). Artificial intelligence in recommender systems. Complex & Intelligent Systems, 7, 439–457. https://doi.org/10.1007/s40747-020-00212-w

Pal, A., Sehgal, P., & Bansal, R. (2025). Enhanced smartphone imaging: Assessment of deep learning based image signal processing pipeline. Digital Signal Processing, 162, 105179. https://doi.org/10.1016/j.dsp.2025.105179

Mohamed, Y. A., Khanan, A., Bashir, M., Mohamed, A. H. H. M., Adiel, M. A. E., & Elsadig, M. A. E. (2024). The impact of artificial intelligence on language translation: A review. IEEE Access, 12, 25553–25575. https://doi.org/10.1109/access.2024.3366802

Malodia, S., Islam, N., Kaur, P., & Dhir, A. (2021). Why do people use Artificial Intelligence (AI)–enabled voice assistants? IEEE Transactions on Engineering Management, 71, 491–505. https://doi.org/10.1109/tem.2021.3117884

Bryman, A. (2016). Social research methods (5th ed.). Oxford University Press.

Groves, R. M., Fowler, F. J., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2009). Survey methodology (2nd ed.). Wiley.

Saunders, M., Lewis, P., & Thornhill, A. (2019). Research methods for business students (8th ed.). Pearson.

Presser, S., Couper, M. P., Lessler, J. T., Martin, E., Martin, J., Rothgeb, J. M., & Singer, E. (2004). Methods for testing and evaluating survey questions. Public Opinion Quarterly, 68(1), 109–130. https://doi.org/10.1093/poq/nfh008

Purnell, D., Jr., Etemadi, A., & Kamp, J. (2024). Developing an early warning system for financial networks: An explainable machine learning approach. Entropy, 26(9), 796. https://doi.org/10.3390/e26090796

Huynh, T., & Uebelmesser, S. (2024). Early warning models for systemic banking crises: Can political indicators improve prediction? European Journal of Political Economy, 81, 102484. https://doi.org/10.1016/j.ejpoleco.2023.102484

Barthélémy, S., Gautier, V., & Rondeau, F. (2024). Early warning system for currency crises using long short-term memory and gated recurrent unit neural networks. Journal of Forecasting, 43(6), 1235–1262. https://doi.org/10.1002/for.3069

Zhang, Z., Zhu, Z., & Hua, Y. (2025). Research on the financial early warning models based on ensemble learning algorithms: Introducing MD&A and stock forum comments textual indicators. PLOS ONE, 20(5), e0323737. https://doi.org/10.1371/journal.pone.0323737

Stander, Y. S. (2024). A News Sentiment Index to Inform International Financial Reporting Standard 9 Impairments. Journal of Risk and Financial Management, 17(7), 282. https://doi.org/10.3390/jrfm17070282

Patel, V. P. (2025, May 16). Explainable AI hits the real world: Spotlight on finance & healthcare. LinkedIn. Retrieved June 20th, 2025, from https://www.linkedin.com/pulse/explainable-ai-hits-real-world-spotlight-finance-healthcare-patel-8rqye

Groves, R. M., Fowler, F. J., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2009). Survey Methodology (2nd ed.). Wiley.

Fan, W., & Yan, Z. (2010). Factors affecting response rates of the web survey: A systematic review. Computers in Human Behavior, 26(2), 132-139. https://doi.org/10.1016/j.chb.2009.10.015

Deutskens, E., de Ruyter, K., Wetzels, M., & Oosterveld, P. (2004). Response Rate and Response Quality of Internet-Based Surveys: An Experimental Study. Marketing Letters, 15(1), 21–36. https://doi.org/10.1023/b:mark.0000021968.86465.00

Alahmari, A. A., Almuzaini, Y., Alamri, F., Alenzi, R., & Khan, A. A. (2024). Strengthening global health security through health early warning systems: A literature review and case study. Journal of Infection and Public Health, 17, 85–95. https://doi.org/10.1016/j.jiph.2024.01.019

Islam, Md. M., Hasan, M., Mia, Md. S., Al Masud, A., & Islam, A. R. M. T. (2025). Early Warning Systems in Climate Risk Management: Roles and Implementations in Eradicating Barriers and Overcoming Challenges. Natural Hazards Research. https://doi.org/10.1016/j.nhres.2025.01.007

Apel, M., Biskup, J., Flegel, U., & Meier, M. (2010). Towards Early Warning Systems – Challenges, Technologies and Architecture. In Lecture Notes in Computer Science (pp. 151–164). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-14379-3_13

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1135–1144. https://doi.org/10.1145/2939672.2939778

Lundberg, S., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions (Version 2). arXiv. https://doi.org/10.48550/ARXIV.1705.07874

Molnar, C. (2022). Interpretable Machine Learning (2nd ed.). Retrieved June 22nd , 2025, from https://christophm.github.io/interpretable-ml-book/

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

APPENDIX

Table 1: Full Survey Questionnaire

1. Respondent Profile
    - What is your current professional role?
    - How many years of experience do you have in the financial sector?
    - How familiar are you with Early Warning Systems for financial risk detection?

2. EWS Usage & AI Adoption
    - Does your institution/you as a researcher currently use an Early Warning System to monitor financial risks?
    - Which types of EWS approaches are primarily used in your institution/personal working space?
    - How effective do you consider current EWS models in predicting financial distress?
    - What do you perceive as the greatest limitation of current EWS frameworks?
    - What is your institution's/personal current level of adoption of AI or machine learning in the general daily workflow? (e.g., using ChatGPT or other programs for writing, generating ideas, etc.)
    - To what extent do you believe AI/ML can enhance traditional Early Warning Systems?
    - Which of the following AI methods do you believe hold the most promise for EWS?
    - What is the most critical requirement for trustworthy AI use in financial EWS, in your opinion?
    - Do you believe the benefits of AI in EWS outweigh the potential risks (e.g., model opacity, bias)?
    - Can you describe an example where an AI-enhanced EWS produced insights/outputs that a conventional EWS missed?
    - Looking ahead 3–5 years, what role do you expect AI to play at/in your institution/role as a researcher?

3. Open Feedback
    - In your opinion, what is the single biggest improvement needed for current EWS frameworks?
    - What suggestions do you have for integrating AI more effectively into Early Warning Systems?

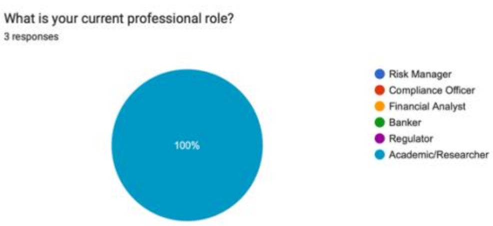

Figure 1: Professional Role

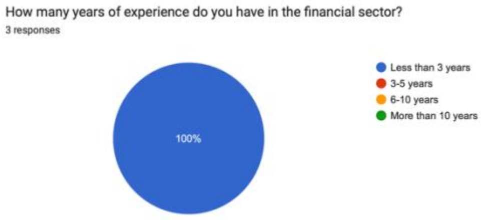

Figure 2: Years of experience

Figure 3: Familiarity with EWS

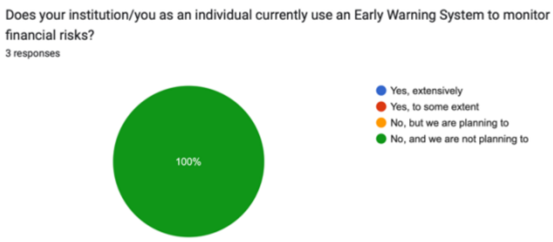

Figure 4: Institution/Individual use of EWS

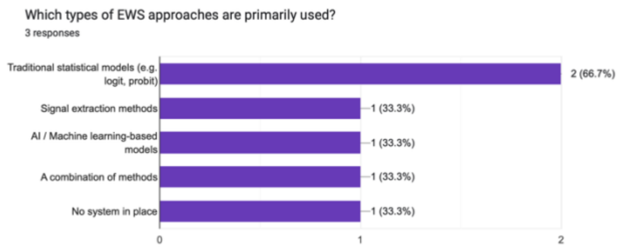

Figure 5: Main types of EWS used

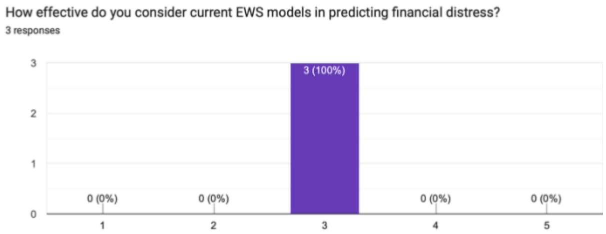

Figure 6: Effectiveness of EWS

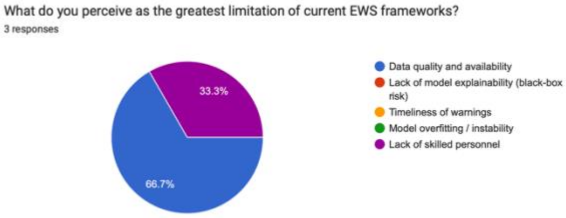

Figure 7: Limitations of EWS

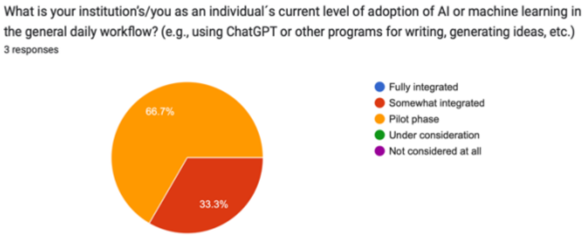

Figure 8: Level of adoption of AI/ML

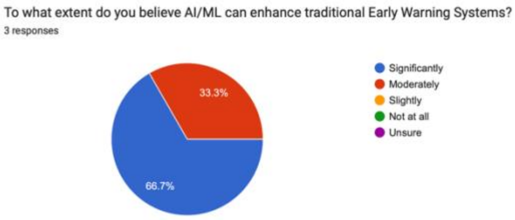

Figure 9: EWS enhancements by AI/ML

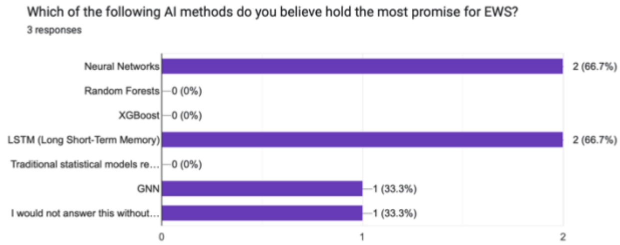

Figure 10: Most promising AI methods

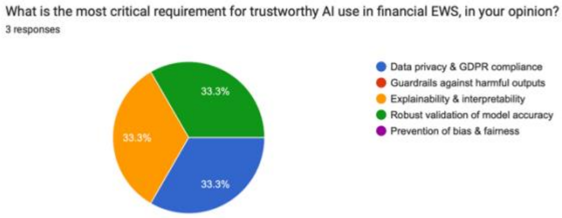

Figure 1: Critical requirement for AI

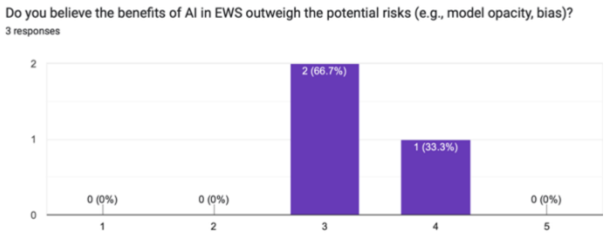

Figure 12: Benefits vs. Risks of AI