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From Weak Signal Detection to Crisis Anticipation: A Systematic Review of Machine Learning Models in Extreme Financial Risk Management

De la détection des signaux faibles à l'anticipation des crises : une revue systématique des modèles d'apprentissage automatique appliqués à la gestion des risques financiers extrêmes

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Abstract

The increasing frequency of extreme financial events has revealed the limitations of traditional risk management approaches in capturing nonlinear dynamics and systemic disruptions. This study aims to examine the contribution of Machine Learning (ML) predictive models to the proactive management of extreme financial risks through a systematic literature review. Based on an analysis of 76 academic studies published between 2010 and 2024, the research identifies the main ML approaches used in risk prediction, including supervised, unsupervised, deep learning, and hybrid models. The findings show that ML techniques significantly improve the detection of weak signals, the anticipation of crises, and the modeling of complex risk dynamics compared with conventional statistical methods. However, several challenges remain, particularly data scarcity, class imbalance, concept drift, model interpretability, and organizational adoption constraints. The review further highlights the growing importance of Explainable Artificial Intelligence (XAI) and adaptive learning approaches in enhancing the reliability and transparency of predictive systems. The study contributes to the literature by proposing an integrated perspective linking predictive performance, explainability, and proactive risk management, while identifying key research directions for the development of more resilient and responsible financial risk management frameworks.

Keywords: Machine Learning; Extreme Financial Risks; Proactive Risk Management; Explainable Artificial Intelligence; Financial Stability.

Résumé

La fréquence croissante des événements financiers extrêmes a mis en évidence les limites des approches traditionnelles de gestion des risques pour appréhender les dynamiques non linéaires et les perturbations systémiques. Cette étude analyse la contribution des modèles prédictifs de Machine Learning (ML) à la gestion proactive des risques financiers extrêmes à travers une revue systématique de la littérature. À partir de l'analyse de 76 publications scientifiques parues entre 2010 et 2024, la recherche identifie les principales approches mobilisées, notamment l'apprentissage supervisé, non supervisé, le Deep Learning et les méthodes hybrides. Les résultats montrent que ces techniques améliorent significativement la détection des signaux faibles, l'anticipation des crises et la modélisation des dynamiques complexes du risque par rapport aux méthodes statistiques traditionnelles. Toutefois, plusieurs défis persistent, notamment la rareté des données, le déséquilibre des classes, le concept drift, l'interprétabilité des modèles et les contraintes organisationnelles d'adoption. L'étude met également en évidence le rôle croissant de l'Intelligence Artificielle Explicable (XAI) et des approches d'apprentissage adaptatif dans le renforcement de la fiabilité et de la transparence des systèmes prédictifs. Elle propose enfin une perspective intégrée reliant performance prédictive, explicabilité et gestion proactive des risques financiers extrêmes.

Mots-clés : Machine Learning ; Risques financiers extrêmes ; Gestion proactive des risques ; Intelligence artificielle explicable ; Stabilité financière.

Introduction

Over the past two decades, global economic and financial systems have been exposed to a succession of major shocks characterized by increasing intensity and limited predictability, such as stock market crashes associated with the COVID-19 pandemic (2020) and recent geopolitical turbulences with global market repercussions. According to Taleb (2007), these so-called Black Swan events are highly improbable, have massive impacts, and are often rationalized ex post, making their anticipation particularly challenging for traditional risk management tools.

The growing prominence of extreme risks has been evidenced by episodes of extreme market volatility, irrational financial behaviors, systemic propagation mechanisms, and stress-testing scenarios. Although statistically rare, these high-impact events generate disproportionate consequences, undermining the stability of institutions, firms, and, more broadly, the resilience of economic systems. As highlighted by Danielsson et al. (2016), "risk management models are typically calibrated on moderate historical data, making them poorly suited to capture the extreme tails of loss distributions."

In a financial environment characterized by increasing structural uncertainty, proactive risk management has become a strategic priority. It involves not only the detection of weak signals that may precede disruptions but also the modeling and anticipation of extreme events, thereby providing decision-makers with robust decision-support tools. However, traditional forecasting approaches, based on statistical models such as Value-at-Risk (VaR) or GARCH models, rely on linear, stationary, and Gaussian assumptions that are often inadequate for capturing the complexity of extreme dynamics. This calls for a renewal of both theoretical and practical modeling frameworks.

Among the proposed solutions, predictive Machine Learning models have emerged as particularly promising tools. Owing to their ability to learn from complex and large-scale data, identify nonlinear patterns, and adapt to unstable environments, these models offer enhanced performance in detecting weak signals and forecasting disruptions (Zhang et al., 2020). Numerous studies (Agarwal et al., 2021; Ghosh et al., 2022) demonstrate that Machine Learning models often outperform traditional approaches in bankruptcy prediction, portfolio management under uncertainty, and dynamic stress testing. These algorithms thus contribute to rethinking the modeling of extreme risks from a predictive perspective. However, this algorithmic power is accompanied by new requirements, particularly in terms of transparency and interpretability. These issues are especially critical in vulnerable contexts such as small and medium-sized enterprises (SMEs) and emerging markets, where understanding underlying mechanisms is as important as predictive accuracy.

In this context, the present study proposes a systematic review of the scientific literature on the contributions of predictive Machine Learning models to the proactive management of extreme financial risks, while integrating the dimensions of prediction, explainability, and practical application.

This review seeks to address the following central research question:

"To what extent do predictive Machine Learning models contribute to a proactive, explainable, and context-aware management of extreme financial risks?"

This main question is complemented by several sub-questions:

- What types of extreme risks are primarily addressed in the literature?
- What characterizes the proactive approach to risk management?
- Which Machine Learning models are most frequently used to predict extreme risks?
- What practical application perspectives emerge, particularly for vulnerable actors such as SMEs?

Despite the growing body of literature on Machine Learning applications in financial risk management, existing studies remain fragmented across different risk categories, methodological approaches, and application contexts. Most previous reviews focus either on the predictive performance of specific algorithms or on particular risk domains, such as credit risk, fraud detection, or market forecasting. Consequently, limited attention has been paid to the integrated relationship between predictive performance, explainability, and proactive management of extreme financial risks. Furthermore, the methodological, organizational, and ethical conditions that determine the effectiveness of ML-based risk management systems remain insufficiently synthesized. This study addresses this gap by providing a systematic and integrated review of the literature, combining insights from risk management, Machine Learning, Explainable Artificial Intelligence (XAI), and complex adaptive systems perspectives. In doing so, it proposes a comprehensive analytical framework for understanding how ML can support a proactive, explainable, and resilient approach to extreme financial risk management.

The objectives of this article are threefold:

- To provide a comprehensive overview of recent contributions in this field;
- To analyze the different algorithms employed and the interpretability dimensions they incorporate;

- To identify key methodological challenges and outline future research directions.

Theoretical Contributions

The present study contributes to the literature in several ways. First, it moves beyond algorithm-centered analyses by proposing an integrated perspective that links Machine Learning capabilities with the principles of proactive extreme financial risk management. Second, it highlights the critical trade-off between predictive performance and explainability, identifying this balance as a central condition for the effective adoption of ML-based risk management systems. Third, the study synthesizes insights from financial risk management, Explainable Artificial Intelligence (XAI), and complex adaptive systems perspectives to develop a comprehensive conceptual framework for understanding the mechanisms through which Machine Learning supports anticipation, resilience, and adaptive decision-making in highly uncertain environments. By doing so, this review contributes not only to the consolidation of existing knowledge but also to the advancement of a more coherent theoretical understanding of ML-driven proactive risk management.

1. Research Methodology

This study adopts a systematic literature review approach inspired by the principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), with the objective of ensuring transparency, rigor, and reproducibility in the identification and selection of relevant studies. Rather than conducting a strict PRISMA-based review, the framework was used as a methodological guide to structure the search, screening, and selection processes.

The methodology adopted in this study is grounded in the principles of systematic literature reviews (Tranfield, Denyer & Smart, 2003; Kitchenham & Charters, 2007). It combines descriptive, bibliometric, and conceptual analyses to provide a comprehensive understanding of the contribution of Machine Learning models to proactive extreme financial risk management. The screening process involved a progressive assessment of the retrieved publications based on predefined inclusion and exclusion criteria. Titles, abstracts, and, where necessary, full texts were examined to evaluate their relevance to the research objectives. Particular attention was given to studies explicitly addressing predictive Machine Learning applications in financial risk management. This iterative selection process resulted in a final corpus of 76 studies considered sufficiently relevant for in-depth analysis.

Bibliographic data were collected from major academic databases, including Web of Science, Scopus, IEEE Xplore, ScienceDirect, and Google Scholar, which are widely recognized for their quality and international coverage. The search strategy relied on combinations of keywords in both English and French, such as Machine Learning, Predictive Models, Financial Risk Management, Extreme Risks, Stress Testing, and Proactive Risk Management, along with their French equivalents. These keywords were applied to titles, abstracts, and keywords of the selected publications.

The search was limited to academic publications (journal articles and conference papers) published between 2010 and 2024, in either English or French. Following the application of this search strategy, an initial corpus of 512 articles was identified. After removing duplicates and screening titles and abstracts based on predefined inclusion and exclusion criteria, a final sample of 76 relevant studies was retained for in-depth analysis.

The analysis was conducted in two main stages. The first stage involved a descriptive analysis, examining the temporal distribution of publications, the most prolific authors and institutions, and the most representative journals. The second stage consisted of a conceptual analysis, focusing on the identification of recurring themes, methodological approaches, and key challenges highlighted in the selected studies.

The analysis was supported by specialized bibliometric tools, including Bibliometrix (R package) and VOSviewer, which enabled the visualization of keyword co-occurrence networks, co-authorship structures, and co-citation patterns, as well as the identification of dominant thematic clusters (Aria & Cuccurullo, 2017; Cobo et al., 2011).

Finally, to enhance the reliability and robustness of the findings, the results were cross-validated against recent methodological recommendations in systematic and bibliometric reviews in management research (Dwivedi et al., 2021; Hilmi & Helmi, 2024).

Table N°1: Summary of the Methodological Framework

Step	***Description***
Review Objective	To identify, analyze, and synthesize academic contributions on predictive Machine Learning models applied to the proactive management of extreme financial risks.
Time Period	Publications between 2010 and 2024.
Data Sources	International academic databases: Web of Science, Scopus, IEEE Xplore, ScienceDirect, Google Scholar.
Keywords	Machine Learning, Predictive Models, Financial Risk Management, Extreme Risks, Stress Testing, Proactive Risk Management (and French equivalents).
Inclusion Criteria	Peer-reviewed academic articles in English or French, with empirical or theoretical validation, explicitly addressing ML in proactive financial risk management.
Exclusion Criteria	Non-financial studies, non-predictive approaches, non-academic sources, or studies lacking direct relevance.

Analysis Tools	Qualitative analysis grid inspired by Denyer & Tranfield (2009); bibliometric tools (Bibliometrix, VOSviewer).
Types of Analysis	Descriptive (volume, time, authors, sources) and conceptual (methods, themes, challenges, and perspectives).

Source: Author's Elaboration.

This methodological approach, combining rigorous literature review with bibliometric and conceptual analysis, ensures the transparency, robustness, and relevance of the findings presented in this study.

2. Structure of the Article

Through this study, we aim to provide an in-depth and critical analysis of recent developments in Machine Learning algorithms applied to the proactive management of extreme financial risks. The article highlights both the potential contributions of these tools in terms of prediction and decision support, as well as the methodological and operational challenges that hinder their large-scale adoption.

First, we propose a structuring conceptual framework by defining the fundamental notions related to extreme risks, their typology, and the principles of proactive management. Next, we analyze the main Machine Learning approaches mobilized in the literature, emphasizing their ability to capture the complexity of extreme dynamics while examining the interpretability dimensions they incorporate.

We then further investigate the factors influencing the performance of these algorithms, particularly in contexts characterized by high vulnerability, such as SMEs and volatile markets. Finally, we identify persistent methodological gaps and propose future research directions aligned with the requirements of robustness, transparency, and contextualization inherent to the management of extreme risks.

3. Conceptual and Theoretical Framework

3.1. Complex Adaptive Systems Perspective

This review is primarily grounded in the Complex Adaptive Systems (CAS) perspective, which provides a relevant theoretical framework for understanding the dynamics of extreme financial risks. Financial systems can be viewed as complex adaptive systems characterized by nonlinear interactions, feedback mechanisms, interconnected actors, and continuous adaptation to changing environments. Within such systems, extreme financial events emerge from the interaction of multiple factors and often remain difficult to anticipate using traditional linear risk models. From this perspective, proactive risk management requires the ability to identify weak signals, detect emerging vulnerabilities, and adapt decision-making processes in real time.

Machine Learning technologies are particularly relevant in this context because they enhance the capacity of organizations to process complex information, recognize hidden patterns, and anticipate systemic disruptions. The CAS perspective therefore serves as the overarching theoretical lens connecting extreme financial risks, proactive risk management, explainable artificial intelligence, and predictive analytics throughout this review.

This study adopts the Complex Adaptive Systems (CAS) perspective as its primary theoretical lens for understanding the role of Machine Learning in extreme financial risk management. Financial systems are increasingly recognized as complex adaptive environments characterized by nonlinear interactions, feedback loops, interconnected agents, and continuous adaptation to changing economic conditions. Within such systems, extreme financial events rarely emerge from isolated causes; rather, they result from the dynamic interaction of multiple factors whose collective behavior is often difficult to predict using traditional linear models.

From a CAS perspective, risk is viewed as an evolving and emergent phenomenon shaped by uncertainty, interdependence, and systemic complexity. This theoretical lens provides a relevant foundation for understanding why conventional risk management approaches frequently struggle to anticipate crises and rare events. In contrast, Machine Learning techniques offer the ability to process large volumes of heterogeneous data, identify weak signals, and detect hidden patterns that may precede systemic disruptions.

Accordingly, the integration of Machine Learning into proactive risk management can be interpreted as an adaptive response to the increasing complexity of contemporary financial systems. The CAS framework therefore serves as a conceptual bridge linking predictive analytics, organizational resilience, and anticipatory decision-making in the management of extreme financial risks.

3.2.Extreme Financial Risks: Nature & Dynamics

Extreme financial risks refer to low-probability, high-impact events capable of severely disrupting the stability of economic and financial systems. Unlike conventional risks, such events, ranging from systemic crises to cascading institutional failures, fall outside the assumptions of normality that underpin most traditional financial models (Danielsson et al., 2016).

From a theoretical standpoint, extreme risks are characterized by nonlinear dynamics, regime shifts, and systemic interdependencies, making them inherently difficult to capture using linear or distribution-based frameworks (Embrechts et al., 1997; Danielsson et al., 2016).

These risks are characterized by nonlinear dynamics, systemic interdependencies, and regime shifts, making them difficult to model using conventional approaches (Embrechts et al., 1997; Danielsson et al., 2016). Moreover, behavioral factors such as herding behavior and panic, play a crucial role in amplifying financial instability (Shiller, 2003; Taleb, 2007).

In addition to these structural properties, the behavioral dimension constitutes a critical driver of extreme risk formation and propagation. Behavioral finance literature highlights how collective irrationality, such as panic, herding behavior, and speculative exuberance, can amplify initial shocks and transform localized imbalances into systemic crises (Shiller, 2003; Taleb, 2007). In this regard, extreme events are not purely exogenous but often emerge endogenously from within the financial system itself.

Traditional risk measurement tools, particularly those based on Value at Risk (VaR) and GARCH-type models, exhibit significant limitations in capturing extreme risk exposure. Their reliance on restrictive distributional assumptions and their inability to adequately model fat tails or abrupt regime changes reduce their effectiveness in turbulent environments (McNeil et al., 2015). To overcome these shortcomings, alternative approaches such as Extreme Value Theory (EVT) and stress testing frameworks have been developed to better account for tail risks and catastrophic scenarios (Glasserman et al., 2015).

However, these approaches remain largely deterministic and dependent on predefined assumptions, which limits their adaptability in real-time and their capacity to capture evolving risk structures in highly volatile and uncertain contexts. This limitation is particularly critical in contemporary financial environments characterized by increasing interconnectedness, rapid information diffusion, and heightened systemic vulnerability.

The literature identifies several categories of extreme financial risks, including liquidity shocks, systemic failures, speculative bubbles followed by crashes, and exogenous macroeconomic shocks related to health, geopolitical, or environmental crises (Taleb, 2007; Acharya et al., 2010). These risks are deeply interconnected and often co-evolve with the behavior of economic agents, further complicating their anticipation and management.

Consequently, the growing complexity and multidimensionality of extreme risks call for a fundamental rethinking of risk detection and management frameworks. This involves moving beyond static and linear approaches toward more flexible, data-driven, and adaptive methodologies capable of integrating nonlinearity, endogeneity, and radical uncertainty.

To synthesize these dimensions, Table 2 presents a structured typology of extreme financial risks, highlighting their conceptual specificity and their theoretical anchoring within the literature.

Table N°2: Typology of Extreme Financial Risks

Type of Extreme Risk	*Description*
Extreme Liquidity Shock	Sudden inability to meet financial obligations, typically arising in contexts of panic or interbank market disruptions *(Acharya & Pedersen, 2005).*
Systemic Failure Risk	Collapse of one or more major financial institutions, triggering a domino effect across the entire system *(Acharya et al., 2010).*
Stock Market Crash Risk	Abrupt and large-scale decline in asset prices, often linked to speculative bubbles or external shocks *(Kindleberger & Aliber, 2011).*
Financial Contagion Risk	Transmission of localized shocks across markets or institutions through financial linkages or behavioral channels (*Kaminsky, Reinhart & Végh, 2003).*
Exogenous Macroeconomic Risk	Risks originating from external shocks such as pandemics, geopolitical conflicts, or environmental crises *(Baker et al., 2020).*
Extreme Behavioral Risk	Market dysfunction driven by irrational behaviors such as panic, herding, or speculative excess (*Shiller, 2003).*
Extreme Regulatory or Institutional Risk	Sudden changes in financial or economic rules (e.g., asset freezes, nationalization, sovereign default) *(Reinhart & Rogoff, 2009).*

Source: Author's Elaboration.

3.3.From Reactive to Proactive Management of Extreme Risks

Risk management has evolved from a reactive approach focused on ex post loss mitigation toward a proactive paradigm emphasizing anticipation and adaptation (Dionne, 2013). Its fundamental objective remains the maximization of firm value through the minimization of risk-related costs (Dionne, 2013). However, the increasing complexity of financial systems and the emergence of extreme risks have exposed the structural limitations of traditional approaches.

Historically, financial risk management has been predominantly rooted in a reactive paradigm, focused on the measurement, monitoring, and mitigation of risks after their occurrence. This approach relies heavily on historical data, past volatility assessments, and the modeling of loss distributions under normal market conditions. The dominant tools, stemming from classical probabilistic frameworks, include scoring models (Altman, 1968), structural credit risk models (Merton, 1974), Value at Risk (VaR) (Jorion, 2007), and conditional correlation matrices (Alexander, 2008). While these models have long structured the field, they have proven inadequate in the face of extreme risks, which are characterized by rarity, severity, and their propensity to disrupt standard market dynamics (Embrechts et al., 1997; Taleb, 2007).

Traditional models rely on historical data and probabilistic assumptions, limiting their effectiveness in volatile environments. In contrast, proactive risk management focuses on detecting weak signals and enhancing system resilience (Aven, 2015). Such an approach aims to enhance system resilience under conditions of radical uncertainty by mobilizing dynamic and adaptive tools.

Machine Learning algorithms plays a central role in this transition by enabling real-time analysis, pattern recognition, and early warning detection in complex environments (Zhang et al., 2020).

Proactive risk management thus reflects a fundamental shift in paradigm, incorporating the dynamic, uncertain, and inherently nonlinear nature of risk phenomena (Aven, 2016; Power, 2007). It moves beyond the sole estimation of event probabilities toward a broader objective: reducing overall exposure through preventive strategies, strengthening shock absorption capacity, and fostering organizational flexibility in the face of unexpected disruptions.

Recent advances in Machine Learning further reinforce this transition. Unlike traditional approaches, ML algorithms can extract complex patterns from large-scale, heterogeneous, and continuously evolving datasets without relying on restrictive parametric assumptions (Goodfellow et al., 2016; Zhang et al., 2020). This capacity positions them as key enablers of anticipatory and adaptive risk management frameworks, particularly in environments characterized by high volatility, uncertainty, and systemic interconnectedness.

To synthesize these distinctions, Table 3 highlights the fundamental differences between reactive and proactive paradigms, illustrating how contemporary approaches, particularly those based on Machine Learning, align with a forward-looking and adaptive logic better suited to complex financial environments.

Table 03: Distinctive Features of Reactive vs. Proactive Approaches in Extreme Risk Management

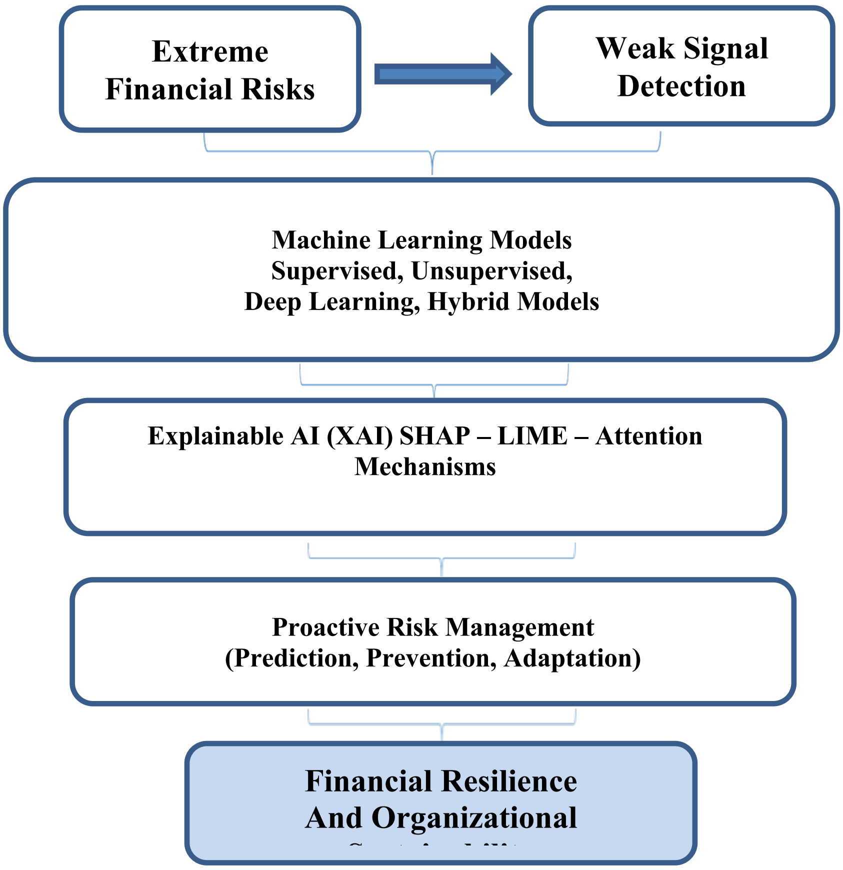
Dimensions	Reactive Risk Management	Proactive Risk Management
Temporality	After the occurrence of risk	Before risk materialization
Objective	Mitigate realized losses	Anticipate and prevent disruptions
Data Used	Historical data, past volatility, observed distributions	Large-scale, heterogeneous, real-time data, including unstructured data
Methods	Classical probabilistic models	Scenario analysis, weak signal detection, Machine Learning,

		Deep Learning
Flexibility & Adaptability	Low, rigid models, limited sensitivity to regime shifts	High, continuous learning and adaptation to evolving conditions
Organizationnal Culture	Focus on compliance, control, and loss mitigation	Focus on vigilance, preparedness, resilience, and adaptive capacity

Source: Author's Elaboration.

3.4. Machine Learning Predictive Models for Proactive Management of Extreme Financial Risks

Figure N° 2: Conceptual Framework Linking Complex Adaptive Systems, Machine Learning, Explainable AI, and Proactive Extreme Financial Risk Management



Source: Author's elaboration

The increasing complexity and instability of financial markets, combined with the occurrence of extreme events with systemic consequences, have fundamentally challenged the effectiveness of traditional risk management tools. In such environments, characterized by nonlinear dynamics, structural breaks, and high uncertainty, conventional econometric approaches often fail to capture the underlying mechanisms driving extreme risk formation and propagation.

In this context, Machine Learning (ML) emerges as a promising alternative, primarily due to its ability to uncover complex and nonlinear patterns within high-dimensional datasets. This makes it particularly well-suited for prediction and anomaly detection in dynamic and uncertain environments (Jordan & Mitchell, 2015). As such, ML constitutes a strategic enabler of proactive risk management, shifting the focus from ex post reaction toward anticipation, early detection, and adaptive decision-making (Khandani, Kim & Lo, 2010).

A growing body of empirical research demonstrates that ML techniques can overcome limitations of traditional econometric models, especially under conditions of high uncertainty and data heterogeneity. Supervised learning approaches enable the prediction of rare events by leveraging labeled and often imbalanced datasets, thereby capturing the asymmetries inherent in extreme loss distributions (Bao et al., 2017; Lessmann et al., 2015). In parallel, unsupervised learning techniques facilitate the detection of latent structures, anomalies, and unexpected behavioral patterns, providing valuable insights into systemic vulnerabilities that remain invisible to conventional methods (Chandola, Banerjee & Kumar, 2009).

Recent advances in Deep Learning have further expanded the analytical capabilities of ML in the context of extreme risk management. Architectures such as Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), and Gated Recurrent Units (GRU) are particularly effective in modeling complex temporal dependencies and nonlinear dynamics within financial time series (Fischer & Krauss, 2018; Nelson et al., 2017; Bao, Yue & Rao, 2017). These models enable the simultaneous integration of heterogeneous data sources, including financial, macroeconomic, and behavioral variables, thus providing a more comprehensive understanding of crisis mechanisms and early warning signals.

Moreover, the integration of hybrid and ensemble methods, combining supervised, unsupervised, and probabilistic approaches, opens new avenues for enhancing organizational resilience. By reconciling analytical robustness with model flexibility, these approaches overcome restrictive parametric assumptions and adapt dynamically to regime shifts and evolving market conditions (Zhang et al., 2020; Ghosh et al., 2022). This adaptability is particularly critical in contexts where extreme events emerge endogenously and are often amplified by collective behavioral dynamics (Taleb, 2007; Shiller, 2003).

From a theoretical perspective, the adoption of Machine Learning reflects a broader transition toward a data-driven and complexity-informed paradigm in financial risk management. Unlike traditional models grounded in equilibrium assumptions, ML approaches align with the principles of complex adaptive systems, where uncertainty, nonlinearity, and emergence are central features. This paradigm shift reinforces the relevance of ML as both an analytical and operational framework for proactive risk management.

The recent literature highlights the diversity of ML techniques mobilized for extreme risk management. These methods differ in their learning paradigms (supervised, unsupervised, deep, or hybrid), analytical capabilities, and application domains (Jordan & Mitchell, 2015; Brynjolfsson & McAfee, 2017). Establishing a structured typology is therefore essential to clarify their respective strengths in addressing radical uncertainty and financial complexity (Varian, 2014).

To synthesize these contributions, Table 4 provides a comprehensive mapping of the most widely used predictive ML models, highlighting their analytical specificities and primary application areas as identified in the literature.

Table N°4: Machine Learning Predictive Models for Proactive Management of Extreme Financial Risks

Category	Representative Methods	Key Characteristics	Type of Risk
Supervised Learning	Logistic Regression, Random Forest, Support Vector Machines (SVM), XGBoos	Based on labeled data; capture relationships between explanatory variables and rare events	Default prediction, bankruptcy forecasting, stress testing, extreme loss prediction *(Lessmann et al., 2015; Bao et al., 2017)*
Unsupervised Learning	K-Means, DBSCAN, Principal Component Analysis (PCA), Autoencoders	No labeled data required; detect latent structures and anomalies	Anomaly detection, behavioral clustering, identification of systemic vulnerabilities *(Chandola et al., 2009; Tsai et al., 2009)*
Deep Learning	CNN, LSTM, RNN, GRU, Transformers	Model complex nonlinear dynamics, leverage large-scale and heterogeneous data	Time series forecasting, extreme scenario simulation, early warning signal detection *(Fischer & Krauss, 2018; Nelson et al., 2017)*
Hybrid & Ensemble Methods	Bagging, Boosting, Stacking, Bayesian ensemble models	Combine multiple models; enhance robustness, flexibility, and adaptability	Modeling fat tails, robustness to regime shifts, high-uncertainty scenario analysis *(Zhang et al., 2020; Ghosh et al., 2022)*

Source: Author's Elaboration.

3.5.Methodological Challenges and Limitations of Predictive Models in Proactive Risk Management

Despite the significant advances of Machine Learning (ML) in the proactive management of extreme financial risks, these approaches are not without limitations, both methodological and operational. While ML models offer enhanced predictive power and flexibility, their deployment in highly uncertain and dynamic financial environments raises critical concerns regarding reliability, interpretability, and robustness.

A growing body of literature emphasizes that the intrinsic complexity of ML models, combined with the rarity of extreme events and the evolving nature of financial markets, poses substantial challenges to their effective implementation (Goodfellow et al., 2016; Doshi-Velez & Kim, 2017). Paradoxically, the use of increasingly sophisticated algorithms may introduce new sources of vulnerability, particularly related to data quality, overfitting, and the opacity of decision-making processes (Rudin, 2019; Liu et al., 2019).

From a critical standpoint, these challenges can be structured around several key dimensions, reflecting the fundamental trade-offs between model complexity, predictive performance, and operational applicability.

3.5.1. Data-Related Constraints

One of the primary challenges in modeling extreme financial risks lies in the scarcity and low frequency of extreme events, which makes the construction of representative datasets particularly difficult (Boudt et al., 2013). In most cases, available datasets are highly imbalanced, with extreme events representing only a marginal proportion compared to normal market conditions. This imbalance can bias model training and significantly reduce generalization performance (Liu et al., 2019).

Furthermore, data quality issues constitute a major source of vulnerability. Financial datasets are often affected by outliers, missing values, structural breaks, or measurement errors, all of which can compromise the robustness and stability of predictive models (Tsai et al., 2009). In the context of extreme risks, where tail observations are critical, such imperfections may lead to substantial misestimating and unreliable predictions.

More fundamentally, the increasing reliance on heterogeneous and high-frequency data (including unstructured data such as news or sentiment indicators) introduces additional challenges related to data integration, preprocessing, and noise filtering. These issues highlight the importance of data governance and feature engineering as central components of ML-based risk management frameworks.

3.5.2. Overfitting, Generalization, and Concept Drift

Another major limitation of predictive models in the context of extreme risks is their susceptibility to overfitting, defined as the tendency to memorize training data rather than learn generalizable patterns (Goodfellow et al., 2016; Yoon et al., 2020). This issue is particularly acute when dealing with rare event datasets, where the limited number of extreme observations exacerbates model instability and reduces out-of-sample predictive performance.

This challenge is further intensified in the case of deep learning models, which typically require large volumes of data to achieve robust generalization. As highlighted by Zhang et al. (2021), insufficient data availability in extreme risk contexts may lead to over-parameterized models that perform well in-sample but fail to generalize under new or unseen conditions.

In addition, financial markets are inherently dynamic and subject to structural changes, such as regime shifts, speculative bubbles, or systemic crises. These changes can render previously learned patterns obsolete, a phenomenon commonly referred to as concept drift (Gama et al., 2014; Zliobaitė, 2017). As a result, models trained on historical data may quickly lose their predictive relevance in evolving environments.

Addressing these challenges requires the development of adaptive learning strategies capable of continuously updating model parameters and incorporating new information. In this regard, recent approaches such as transfer learning and ensemble methods have gained increasing attention. Transfer learning enables the reuse of knowledge acquired in one context to improve learning in another (Pan & Yang, 2010; Torrey & Shavlik, 2010), while ensemble techniques enhance robustness by combining multiple models and reducing variance (Tan et al., 2018).

Although these approaches show promising results, their application in the specific context of extreme financial risk management remains relatively underexplored, highlighting an important avenue for future research.

3.5.3. Lack of Interpretability and Transparency

The opacity of complex Machine Learning models often referred to as "black boxes" constitutes a major barrier to their adoption in regulated financial environments, where accountability and decision traceability are essential (Doshi-Velez & Kim, 2017; Rudin, 2019). While these models may achieve high predictive performance, their limited interpretability raises critical concerns regarding trust, validation, and regulatory compliance.

The absence of interpretability complicates the understanding of the underlying mechanisms driving model predictions, thereby reducing their credibility among decision-makers and supervisory authorities (Lipton, 2016). In the context of extreme financial risk management, where decisions may have systemic implications, this limitation becomes particularly problematic. Stakeholders require not only accurate predictions but also clear and actionable explanations of the factors contributing to risk exposure.

From a methodological perspective, this issue reflects a fundamental trade-off between model complexity and interpretability. Highly sophisticated models, such as deep neural networks, are capable of capturing intricate nonlinear relationships but often do so at the expense of transparency. Conversely, simpler models offer greater interpretability but may lack the predictive power needed to capture extreme risk dynamics.

In response to this challenge, the emerging field of Explainable Artificial Intelligence (XAI) seeks to reconcile performance and interpretability by developing techniques that make model outputs more transparent and understandable. Methods such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and attention mechanisms provide insights into feature importance and local decision behavior, thereby enhancing model explainability (Rudin, 2019).

However, despite these advances, interpretability remains a partially unresolved challenge, particularly in high-stakes financial contexts characterized by uncertainty, data complexity, and regulatory scrutiny. This highlights the need for hybrid approaches that balance predictive accuracy with transparency, as well as for the integration of interpretability as a core design principle in ML-based risk management systems.

3.5.4. Organizational Integration Constraints

The adoption of Machine Learning (ML) approaches in financial risk management faces significant organizational barriers that extend beyond purely technical considerations. While ML offers substantial analytical capabilities, its effective implementation requires a supportive organizational ecosystem, encompassing appropriate infrastructure, specialized expertise, and a culture conducive to data-driven decision-making.

In practice, these requirements remain difficult to meet, particularly for small and medium-sized enterprises (SMEs) and organizations operating in emerging economies, where access to advanced technological infrastructures and skilled human capital is often limited (Brock & Khan, 2021; Rai et al., 2021). This structural gap creates asymmetries in the adoption of ML-based risk management practices, potentially reinforcing existing disparities in risk resilience across firms and markets.

Beyond resource constraints, organizational resistance represents a critical challenge. Decision-makers may exhibit reluctance toward adopting ML systems due to a lack of trust, limited understanding of algorithmic processes, or concerns about the loss of human control over strategic decisions (Dwivedi et al., 2021; Shrestha et al., 2021). Such cultural barriers can significantly hinder the integration of ML tools into existing risk management frameworks, even when their technical performance is well established.

Furthermore, the operational deployment of ML models raises important governance and regulatory issues. Ensuring model reliability over time requires continuous monitoring, validation, and updating processes, particularly in dynamic financial environments. This has led to the emergence of Model Risk Management (MRM) frameworks, which emphasize rigorous validation procedures, documentation standards, and auditability requirements (Basel Committee, 2019; Arora & Arora, 2023).

From a broader perspective, these challenges highlight that the integration of ML into proactive risk management is not solely a technological transition but a multidimensional transformation involving technical, organizational, and regulatory dimensions. Achieving effective and sustainable adoption therefore requires a holistic approach that aligns technological capabilities with human competencies, governance structures, and institutional constraints.

4. Epistemological and Ethical Limitations

Beyond technical and organizational constraints, the use of Machine Learning (ML) in proactive financial risk management raises critical epistemological and ethical concerns. From an epistemological perspective, ML models rely heavily on historical data to infer patterns and generate predictions. This dependence raises fundamental questions about the nature and validity of the knowledge produced, particularly in contexts characterized by structural breaks, radical uncertainty, and evolving risk dynamics.

In particular, the reliance on past data may lead to the reproduction or even amplification of pre-existing structural biases embedded within financial systems, thereby compromising both the fairness and robustness of decision-making processes (Mehrabi et al., 2018; Ntoutsi et al., 2020). This issue is especially problematic in high-stakes environments such as financial risk management, where biased predictions can have significant economic and social consequences. Moreover, the emphasis on predictive performance often comes at the expense of qualitative and contextual dimensions that are difficult to quantify, such as organizational resilience, institutional trust, and the behavioral drivers of financial instability (Lepri et al., 2018; O'Neil, 2016). As a result, ML-based approaches may provide technically accurate predictions while overlooking critical underlying mechanisms that shape extreme risk phenomena.

The opacity of certain algorithmic models further exacerbates these concerns. The difficulty in interpreting model outputs, particularly in the case of complex "black-box" systems raises important issues related to accountability, transparency, and explainability, which are essential in regulated financial contexts (Raji & Buolamwini, 2019; Rudin, 2019). In such settings, the inability to justify automated decisions may undermine both regulatory compliance and stakeholder trust.

In addition, the increasing reliance on large-scale and often sensitive datasets introduces significant ethical challenges related to data privacy, surveillance, and the potential misuse of information (Lepri et al., 2018; Floridi & Cowls, 2019). These concerns highlight the need for robust data governance frameworks capable of ensuring responsible data collection, processing, and usage.

Taken together, these limitations call for the development of more responsible and human-centered approaches to ML in financial risk management. This includes the integration of fairness, transparency, and accountability principles into model design and deployment, as well as the adoption of ethical AI frameworks aligned with the rights and interests of stakeholders (Jobin, Lenca & Vayena, 2019; Floridi et al., 2018).

5. Discussion and Research Perspectives

The findings suggest that ML significantly enhances proactive risk management but does not fully replace traditional approaches. This duality suggests that ML-based approaches do not constitute a radical break from existing paradigms, but rather an incremental evolution toward more adaptive, data-driven, and anticipatory risk management frameworks.

On the one hand, supervised learning models appear particularly effective in predicting rare events, especially in contexts where structured and sufficiently rich datasets are available. As demonstrated by Lessmann et al. (2015), these approaches significantly improve the predictive accuracy of scoring models compared to traditional statistical techniques. However, their performance remains highly dependent on data quality and representativeness, which severely limits their applicability in extreme risk environments characterized by scarcity, imbalance, and instability of observations. This dependency raises important concerns regarding model robustness under conditions of radical uncertainty.

On the other hand, unsupervised and hybrid approaches provide a valuable alternative by enabling the identification of latent structures, hidden patterns, and atypical behaviors. In this regard, anomaly detection defined as "the problem of finding patterns in data that do not conform to expected behavior" (Chandola et al., 2009) emerges as a key mechanism for early detection of weak signals and systemic vulnerabilities. Nevertheless, these approaches remain constrained by challenges related to interpretability, validation, and operational integration, particularly in decision-making environments requiring strong justification and accountability. Furthermore, deep learning models have demonstrated strong capabilities in capturing the complex dynamics of financial time series, particularly nonlinear dependencies and long-term temporal relationships. This makes them particularly relevant for modeling structural breaks and extreme market movements. However, their black-box nature remains a major limitation. As emphasized by Rudin (2019), opaque models are often difficult to justify in high-stakes decision contexts, where transparency and explainability are essential. This tension between predictive performance and interpretability constitutes a central challenge in the application of ML to financial risk management.

In this perspective, one of the key contributions of this review is the identification of a necessary trade-off between accuracy and explainability. As highlighted by Doshi-Velez and Kim (2017), interpretability is a fundamental requirement for ensuring trust, accountability, and adoption of ML-based systems. Consequently, the integration of explainability mechanisms is emerging as a promising direction to enhance the operational relevance and legitimacy of predictive models in financial contexts.

Moreover, the effectiveness of ML approaches is strongly conditioned by the application context. In structurally constrained environments, particularly SMEs and emerging economies, adoption depends not only on technological readiness but also on organizational maturity and institutional support. As emphasized by Dwivedi et al. (2021), the successful integration of artificial intelligence requires alignment between technical capabilities, managerial practices, and organizational structures.

From a research perspective, several promising avenues emerge. First, the consideration of regime shifts represents a critical challenge for improving model robustness. The concept of concept drift, defined as the change in statistical properties of data over time (Gama et al., 2014), calls for the development of adaptive models capable of continuously learning and adjusting to dynamic environments.

Second, transfer learning approaches offer a promising solution to the problem of data scarcity in extreme risk contexts. As noted by Pan and Yang (2010), transfer learning enables the reuse of knowledge acquired in related domains, thereby improving predictive performance in data-constrained environments. This approach appears particularly relevant for extreme financial risks, where historical observations are rare and often non-representative.

Finally, ethical and governance considerations constitute an increasingly important research direction. As highlighted by Jobin et al. (2019), the development of AI systems must be grounded in principles of transparency, fairness, and accountability. In financial risk management, these requirements are particularly critical given the systemic implications of algorithmic decisions and their potential socio-economic impact.

Overall, while Machine Learning models offer promising opportunities for advancing proactive financial risk management, their effectiveness ultimately depends on the ability to integrate predictive performance with interpretability, adaptability, and responsible governance. A holistic and interdisciplinary approach therefore appears essential to fully realize the potential of these technologies in complex and uncertain financial environments.

6. Conclusion

The rapid evolution of economic and financial environments, characterized by increasing uncertainty, structural instability, and the recurrent emergence of extreme risks, calls for a profound rethinking of traditional risk management approaches. In this context, this systematic literature review has highlighted the growing and structuring role of Machine Learning (ML) predictive models in enabling a shift from reactive risk management toward a more proactive, anticipatory, and adaptive paradigm for extreme financial risks.

The findings of this study demonstrates that ML techniques provide unprecedented analytical capabilities, particularly in handling large-scale and heterogeneous datasets, modeling complex nonlinear relationships, and detecting early warning signals of systemic disruptions. These contributions represent a significant advancement over classical econometric approaches, which are often constrained by restrictive assumptions and limited capacity to capture tail events and rare occurrences.

However, the analysis also confirms that the full potential of Machine Learning remains partially unrealized due to persistent methodological and practical challenges. Data scarcity and class imbalance in extreme event contexts, risks of overfitting, and the instability of financial environments under concept drift all limit model robustness and generalization capacity. In addition, algorithmic opacity raises critical concerns regarding interpretability, transparency, and trust particularly in highly regulated financial settings where decision accountability is essential.

Beyond technical limitations, this study emphasizes the decisive role of organizational and institutional factors in the effective integration of ML-based risk management systems. Successful adoption requires not only adequate technological infrastructure and advanced analytical skills, but also a broader organizational transformation toward data-driven decision-making and proactive uncertainty management. These challenges are particularly pronounced in SMEs and emerging economies, where resource constraints and heightened vulnerability further amplify risk exposure.

Furthermore, the ethical and epistemological implications of AI adoption in financial risk management cannot be overlooked. The reliance on historical data, the potential reinforcement of structural biases, and issues related to algorithmic accountability highlight the need for more responsible, transparent, and ethically aligned modeling frameworks.

In this regard, one of the main contributions of this review lies in emphasizing the necessity of an integrative and multidimensional approach to extreme financial risk management. Such an approach goes beyond a purely technological perspective on Machine Learning and incorporates behavioral, organizational, theoretical, and regulatory dimensions into a unified analytical framework.

Finally, this research contributes to the literature by proposing an integrated perspective linking ML capabilities to proactive extreme risk management, while identifying key limitations and research gaps. These include the development of hybrid models that reconcile predictive accuracy with interpretability, the exploration of adaptive learning systems capable of handling regime shifts in real time, and the advancement of empirical studies in highly vulnerable contexts. Moreover, a stronger integration between advances in artificial intelligence and the theoretical foundations of financial economics could further enhance both the analytical rigor and operational relevance of ML-based risk management frameworks.

In conclusion, Machine Learning should not be viewed as a standalone solution, but rather as a strategic enabler of a redefined risk management paradigm, one that is more anticipatory, resilient, and responsible. Its effective contribution will ultimately depend on the ability of researchers and practitioners to address the identified challenges and to design frameworks that are robust, transparent, and aligned with the complexity of contemporary financial systems.

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