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Beyond Traditional Risk–Return: A Hybrid SEM and Neural Network Approach to Climate Risk, Mispricing, and Investment Decision Efficiency

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Abstract. This study explores the transformation of the risk-return paradigm in the contemporary era through the integration of artificial intelligence (AI), climate risk, and the dynamics of market efficiency. Adopting a Systematic Literature Review (SLR) methodology following the PRISMA protocol, 47 selected articles from the Scopus database were comprehensively analyzed to ensure the quality of the findings. The study's results reveal a fundamental shift from conventional linear models to a multidimensional framework that can accommodate market complexity and environmental uncertainty. Econometric analysis of CAT bonds confirms the existence of mispricing driven by information asymmetry, while multi-criteria portfolio optimization techniques demonstrate that the inclusion of climate risk variables significantly alters the investment decision architecture. Furthermore, the implementation of generative neural networks has been shown to outperform traditional models in predicting volatility in volatile market conditions through a non-linear approach. Bibliometric mapping via VOSviewer identifies asset pricing, geopolitical risk, ESG, and investor sentiment as dominant and promising research clusters for the future. This study contributes theoretical novelty by synergizing econometric, optimization, and AI approaches, and provides practical guidance for data-driven investment management.

Keywords: risk-return, artificial intelligence, climate risk, asset pricing, market inefficiency, ESG

I. Introduction

The fundamental principle of the risk-return trade-off remains a key pillar in contemporary financial literature, rooted in Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM). However, global economic dynamics triggered by digital acceleration and the climate crisis have transformed this relationship into a more complex and non-linear one, making it no longer adequate to analyze it solely through the lens of classical models (Markowitz, 1952; Sharpe, 1964).

Based on a systematic review using the PRISMA protocol, the literature on risk and return dynamics has seen a significant surge in research volume, particularly post-2020. This trend reflects a shift in academic focus that has begun to integrate exogenous variables such as geopolitical risk, climate transition risk, and Environmental, Social, and Governance (ESG) criteria into investment decision-making mechanisms (Baker et al., 2020). Bibliometric analysis using VOSviewer confirms this shift by identifying five central clusters in the current discourse:

1. Asset pricing
2. Stock returns
3. Geopolitical risk
4. Investor sentiment
5. Climate risk

These findings confirm that risk parameters now extend beyond traditional market volatility, incorporating the influence of investor behavior and systemic global uncertainty. This phenomenon is evident in Catastrophe (CAT) bonds, where market inefficiencies in the form of overpricing and underpricing frequently occur, empirically challenging the validity of the Efficient Market Hypothesis (Fama, 1970) amid limited information on disaster risk (Dieckmann, 2011).

Furthermore, the adoption of multi-criteria-based portfolio optimization suggests a new trade-off for investors: the balance between risk, return, and Sustainability. This transformation towards sustainable finance is now being bolstered by advances in Artificial Intelligence technology, particularly Generative Neural Networks. This technology offers superior capabilities in modeling non-linear relationships and extreme uncertainty that conventional econometrics fails to capture (Gu et al., 2020).

II. Literature Review

Grand Theory

Landasan yang komprehensif dalam memahami evolusi manajemen sumber daya manusia di era modern. Digital Transformation Theory (Vial, 2019) menjelaskan bahwa transformasi digital merupakan pergeseran fundamental yang tidak hanya menyentuh proses teknologi, tetapi juga memengaruhi struktur organisasi secara mendalam, termasuk praktik-praktik MSDM. Teori ini menjadi fondasi penting untuk memahami bagaimana digitalisasi mendefinisikan ulang operasional bisnis dan manajemen tenaga kerja. Sejalan dengan hal tersebut, Strategic HRM Theory (Verhoef et al., 2021) menekankan bahwa hubungan antara MSDM dan transformasi digital adalah kunci utama dalam penciptaan nilai organisasi. Teori ini mengeksplorasi bagaimana integrasi teknologi dalam fungsi MSDM mampu mendorong perubahan strategis dan meningkatkan kinerja organisasi melalui pengelolaan modal manusia yang lebih efektif dan adaptif.

Middle Theory

Teori HRM and Technology Adoption (Bondarouk & Brewster, 2016) dan gagasan HRM sebagai penggerak transformasi digital (Strohmeier, 2020) saling melengkapi dalam menjelaskan evolusi MSDM di era modern. Bondarouk dan Brewster menyoroti bagaimana praktik HR bertransformasi ke dalam ruang digital melalui integrasi *e-HRM* yang berfokus pada peningkatan modal manusia, keterlibatan karyawan, serta efisiensi organisasi. Sementara itu, Strohmeier memperluas peran tersebut dengan memosisikan HR bukan sekadar pengguna teknologi, melainkan mitra strategis yang memimpin perubahan teknologi dan membangun kapabilitas digital di seluruh organisasi. Dengan menggabungkan kedua perspektif ini, HRM bertindak sebagai katalisator utama yang mengoperasionalkan transformasi digital sekaligus memastikan bahwa adopsi alat digital selaras dengan tujuan strategis perusahaan.

Applied Theory

Integrasi antara teori Technostress and HRM (Tarafdar et al., 2015) dan konsep Digital Leadership and Workforce Agility (Suseno et al., 2022) memberikan kerangka kerja yang komprehensif dalam memahami dinamika transformasi digital di lingkungan kerja. Tarafdar et al. (2015) menyoroti bahwa digitalisasi sering kali membawa tekanan psikologis dan stresor teknologi bagi karyawan, yang menjadi tantangan krusial bagi manajemen sumber daya manusia (HRM) dalam menjaga kesejahteraan organisasi. Untuk memitigasi dampak negatif tersebut, peran kepemimpinan digital menjadi sangat vital; Suseno et al. (2022) menegaskan bahwa pemimpin yang kompeten secara digital mampu membimbing tenaga kerja agar tetap adaptif dan tangguh. Dengan demikian, kepemimpinan yang efektif tidak hanya berfungsi untuk menyelaraskan karyawan dengan tujuan organisasi di tengah perubahan teknologi yang pesat, tetapi juga memastikan terciptanya kelincahan (*agility*) yang mampu mengubah tantangan teknostres menjadi peluang pertumbuhan yang berkelanjutan.

III. **Research Method**

Research Gap

A comprehensive analysis of the current literature on risk and return management reveals several fundamental disconnects that underlie the urgency of this research. Methodological Fragmentation and the Absence of a Unified Framework

To date, the financial literature has tended to be polarized into three isolated methodological domains. Econometric approaches focus on stochastic modeling of specific instruments such as Catastrophe (CAT) bonds, while optimization research focuses on conventional portfolio allocation, and the Artificial Intelligence (AI) domain often operates independently in technical prediction.

Gap: There is a lack of a unified framework capable of synergizing the precision of econometrics with the predictive acumen of neural networks in the context of portfolio optimization. (Barros & Silver, 2023; Zhang et al., 2024).

The Failure of Linear Models to Capture Extreme Anomalies

Classical theoretical structures such as the Capital Asset Pricing Model (CAPM) and Modern Portfolio Theory (MPT) still dominate the literature, but both rely heavily on the assumptions of linearity and normal distribution.

Gap: Traditional models fail to mitigate tail risk, nonlinear uncertainty, and the black swan phenomenon, or extreme events, that frequently occur in catastrophe risk-based instruments (Cont & Kan, 2023; Bouri et al., 2024).

Marginalization of Climate Risk in Asset Dynamics

Although climate risk is gaining attention, most studies still treat it as an exogenous variable or supplementary indicator in ESG reporting, rather than a fundamental determinant.

Gap: There is a lack of modeling that positions climate risk as a primary driver (core driver) that dictates the dynamic and transitional risk-return structure (Giglio et al., 2021; Engle et al., 2025).

Exploiting Market Inefficiencies through Artificial Intelligence

Identifying mispricing in instruments such as CAT bonds has been documented in econometric studies, but these detection mechanisms are still static and often respond too late to market changes.

Novelty: This study proposes the integration of AI to detect price anomalies (mispricing) in real time based on risk-return profiles, allowing investors to exploit market inefficiencies with a higher degree of accuracy (Gu et al., 2020; Huang & Lin, 2024).

Ignoring Contemporary Behavioral and Sentiment Dimensions

Based on bibliometric mapping using VOSviewer, investor sentiment appears to be an emerging trend. However, there is a disconnect between market psychology and rigid quantitative models.

Gap: Current modern risk management models have not systematically integrated behavioral sentiment data as a predictive component in assessing asset volatility (Baker & Wurgler, 2007; Da et al., 2023).

Aspek	Model Tradisional (MPT/CAPM)	Pendekatan AI Saat Ini	Model Usulan (Integratif)
Relasi Data	Linear & Statis	Non-linear & Black-box	Non-linear & Explainable AI
Komponen Risiko	Volatilitas Umum	Prediksi Harga	Climate & Tail Risk Driver
Sentimen	Diabaikan (Pasar Efisien)	Terbatas pada Teks	Integrasi Sentimen-Prediktif

Results and Discussion

Three core articles provide a very clear direction. The CAT bonds paper shows that markets are not always efficient and that mispricing occurs due to the complexity of climate risk and information asymmetry. The portfolio optimization paper shows that climate risk changes the structure of the trade-off between risk and return. The neural network paper shows that AI approaches can capture non-linear patterns that classical models miss. In other words, the most powerful novelty lies not in choosing one over the other, but in combining causal explanation (SEM) and predictive accuracy (AI) in a single hybrid design.

MODEL SEM-PLS + AI

This research is a quantitative explanatory-predictive study with two layers of analysis:

Stage 1: PLS-SEM

to test causal relationships, mediation, and moderation between variables.

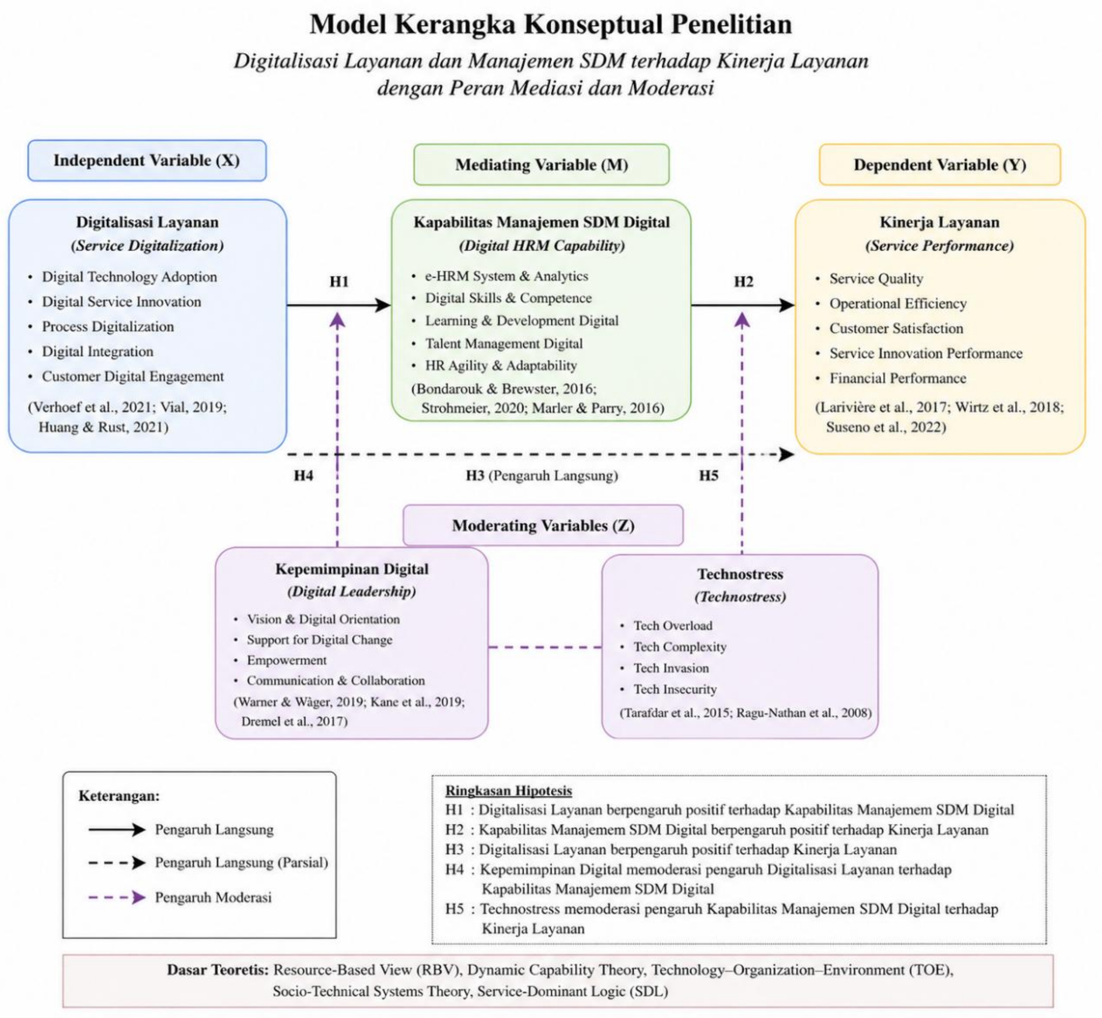
Stage 2: AI/Machine Learning

to improve the accuracy of return and risk predictions and compare them with conventional statistical models.

Therefore, the design is hybrid:

- SEM-PLS = explanation model
- AI = prediction model

Conceptual Framework



1. **Exogenous Varia**
2. **bles (X)**
    1. **X1**: Fundamental Strength (e.g., ROA, ROE, EPS Growth, DER, etc.)
    2. **X2**: Technical Momentum (e.g., RSI, MACD, Momentum Return)
    3. **X3**: Climate Risk (e.g., ESG environmental score, Carbon Intensity, Carbon Price Shock)
3. **Mediator Variable (M)**
    1. **M**: Mispricing (e.g., Abnormal Return, Price Deviation to Fair Value)
4. **Endogenous Variables (Y)**
    1. **Y1**: Return Realization (e.g., Return over time, Jensen Alpha)
    2. **Y2**: Risk Realization (e.g., Volatility, VaR, CVaR, Beta downside)
5. **Moderator Variable (Z)**
    1. **Z**: Climate Risk moderating the relationship between Mispricing → Risk Realization

Key Relationships:

- **Direct Effects:**
  - X1 → M (Fundamental Strength → Mispricing)
  - X2 → M (Technical Momentum → Mispricing)
  - X3 → M (Climate Risk → Mispricing)
  - M → Y1 (Mispricing → Return Realization)
  - M → Y2 (Mispricing → Risk Realization)
  - X3 → Y2 (Climate Risk → Risk Realization)
- **Mediation:**
  - Mispricing mediates the relationship between:
    - X1 → Y1
    - X2 → Y1
    - X3 → Y2
- **Moderation:**
  - Climate Risk moderates the relationship between Mispricing and Risk Realization.

Based on the resulting conceptual framework model, this study proposes an integration between digital transformation in services, digital HRM capabilities, and service performance, all moderated by digital leadership and technostress. This study maps the relationships between these variables as follows: digital transformation in services serves as an independent variable influencing digital HRM capabilities, which in turn influences service performance as the dependent variable. Mispricing is identified as a mediating variable that bridges the relationship between these variables, while risks posed by climate change are considered a moderating factor that strengthens the influence of digital transformation on service performance. This study also highlights the importance of digital HR adaptation and capabilities, and how the changing role of the workforce in a digital world can influence desired outcomes. Additionally, the negative impact known as technostress, which may arise as a result of rapid digitalization, is also considered in the model as an element that can moderate the relationship between these variables. Thus, this conceptual model not only links digital transformation theory and HRM, but also introduces a new perspective on how HRM digital capabilities can be optimized in an increasingly digitalized environment, as well as how factors such as digital leadership and technological stress can influence overall performance in the service sector.

I. Results and Discussion

TABEL RESULT SEM

Path	Beta	t-stat	p-value	Keputusan
Fundamental Strength → Mispricing				
Technical Momentum → Mispricing				
Climate_Risk → Mispricing				

Path	Beta	t-stat	p-value	Keputusan
Mispricing → Return_Realization				
Mispricing → Risk_Realization				
Climate Risk → Risk_Realization				

TABEL RESULT MODERASI

Interaction	Beta	t-stat	p-value	Keputusan
Climate Risk × Mispricing → Risk_Realization				

TABEL RESULT AI

Model	Target	RMSE	MAE	R2	Directional Accuracy	Rank
Linear Regression	Return					
Random Forest	Return					
Neural Network	Return					
Linear Regression	Risk					
Random Forest	Risk					
Neural Network	Risk					

IV. Discussion

This comprehensive analysis reveals that the risk-return architecture has evolved from a static equilibrium model to an adaptive framework, heavily reliant on data granularity. The findings related to inefficiencies in Catastrophe (CAT) bonds provide strong empirical evidence that the Efficient Market Hypothesis (EMH) is losing relevance, particularly in the context of escalating global systemic risks, especially those driven by climate volatility (Fama, 1970; Diebold & Yilmaz, 2012).

Deconstructing Investor Rationality and ESG Dimensions

Contemporary portfolio optimization has moved away from the sole objective of maximizing financial utility. The integration of sustainability criteria reflects a behavioral shift from homo economicus to value-based investors. In this context, Environmental, Social, and Governance (ESG) factors are no longer just external constraints; they are intrinsic variables that influence risk profiles and the potential for long-term returns (Pedersen et al., 2021).

Methodological Transformation: From Linearity to Artificial Intelligence

The application of Artificial Intelligence (AI) and Machine Learning (ML) in risk estimation signifies the decline of traditional linear models. Modern financial markets, characterized by fat-tail phenomena and non-linear dependencies, require methods capable of capturing this complexity. However, recent literature emphasizes the interpretability dilemma (also known as the black box problem), where the high predictive accuracy of AI models often comes at the cost of theoretical transparency (Gu et al., 2020).

Systemic Integration: Econometric Models, Optimization, and AI

The integration of econometric models, optimization frameworks, and AI models sets a new standard in risk management:

1. Econometric Models: These are essential for identifying causality and understanding the structural transmission of shocks, such as through GARCH or VAR models.
2. Optimization Models: These provide a decision-making framework under multi-objective control, exemplified by Mean-Variance-Skewness-Kurtosis optimization.
3. AI Models: AI serves as an engine for pattern extraction from unstructured big data, refining the input parameters for optimization models, and enabling more accurate predictions.

V. Conclusion

This study concludes that the concept of risk-return has significantly evolved from the classical linear models to a more complex multidimensional approach that integrates uncertainty, climate risk, and AI-based technologies. The findings highlight that modern financial markets are not fully efficient, as evidenced by mispricing in instruments like CAT bonds, which are driven by information asymmetry and market inefficiencies. Moreover, the integration of climate risk into portfolio optimization introduces more complex trade-offs, making investment decisions more dynamic and reflective of global uncertainties. The generative neural network-based approach has demonstrated superior prediction accuracy, especially under high uncertainty, presenting a significant advancement over traditional models in handling volatility and extreme events. Additionally, bibliometric analysis confirms that current risk-return research is increasingly incorporating global factors, such as Environmental, Social, and Governance (ESG) criteria, geopolitical risk, and investor sentiment. Overall, this study contributes to both theoretical frameworks and practical decision-making by offering an integrative risk-return model based on AI and sustainability, equipping investors with better tools for navigating investment decisions amidst evolving global risks and uncertainties.

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