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Modeling volatility with multivariate GARCH models through the integration of deep Learning: A literature review

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Abstract:

This paper presents a literature review that examines how deep learning methodologies have been integrated into multivariate GARCH models. While traditional GARCH-type models have long been used to capture time-varying volatility and spillover effects, their parametric and linear nature limits their capacity to reflect the increasing complexity and non-linearity in financial markets. Recent advances in deep learning, notably recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures, provide powerful tools for modeling volatility dynamics and incorporating exogenous information. Based on a critical synthesis of the recent literature, this review outlines the conceptual foundations of hybrid deep learning–GARCH models, compares their methodological benefits and limitations, and identifies key research gaps. The aim is to offer a clear overview of the current state of research and to guide future studies in developing more flexible and accurate volatility forecasting models.

Keywords : Volatility modeling, Multivariate GARCH, Deep learning, Hybrid models, Financial econometrics.
Classification JEL : C58; C45; C53; C22; G17
Paper type : Theoretical Research or Empirical Research

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1. Introduction

Financial markets have become more intricate and interdependent in recent decades, as indicated by greater globalization, advancement in technologies, and information dissemination (Forbes & Rigobon, 2002; Kaminsky & Reinhart, 2000; Goodell & Goutte, 2021), affecting the evolution of risk, uncertainty, and opportunity, creating uncertainty for market participants, and renewing an interest in modeling and forecasting volatility for academics, practitioners and regulators (Bauwens et al., 2006; Francq & Zakoïan, 2010). Volatility, as a measure of variability or uncertainty in asset prices, characterizes behaviors in risk management, asset allocation, derivative-pricing, financial stability, and monetary policy.

The objective of this paper is to review and synthesize recent academic contributions on the integration of deep learning methods especially LSTM and RNN with multivariate GARCH models for financial volatility modeling. This narrative review addresses methodological developments, advantages, challenges, and future directions in the literature.

Econometric modeling of volatility has persisted since it was implemented by Bollerslev (1986) with his GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model. It focuses on the autoregressive conditional heteroskedasticity (ARCH) mechanism (Engle, 1982). GARCH models have defined both the clustering and persistence of volatility in financial time series, an empirical fit of asset returns with substantial rigor (Silvennoinen & Teräsvirta, 2009; Francq & Zakoïan, 2010). GARCH-type models with modeling have become common practice in both academia and industry, with their results being evaluated for their statistical properties, interpretability, and formatting flexibility, which allow for the measurement of risk progression over time (Nguyen et al., 2024). However, given the remarkable speed and scale of modern financial systems, the need for flexibility in standard GARCH-type models has become apparent. Modern financial markets are often nonlinear and experience sudden regime shifts, structural breaks, and are constantly subject to new external shocks (e.g., macroeconomic announcements, geopolitical events, social media, high-frequency trading information, etc.) (Goodfellow et al., 2016). Although classical models use parametric and linear systems that are easier to use, this significantly limits their ability to account for this level of complexity and to use the different types of information available to them (Bauwens et al., 2006; Francq & Zakoïan, 2010; Fischer & Krauss, 2018).

Due to these factors, there has been growing interest in the implementation of machine learning (ML) methodologies, particularly deep learning (DL), for financial time series modeling (Goodfellow et al., 2016; Lecun et al., 2015; Fischer and Krauss, 2018). Deep learning algorithms, in particular recurrent neural networks (RNNs) and short- and long-term memory architectures (LSTM) architectures (Hochreiter & Schmidhuber, 1997), have proven effective in efficiently analyzing sequential, multidimensional, and nonlinear data, a combination that is particularly useful for modeling the challenges inherent in volatility (Chen et al., 2015; Kim and Won, 2018). Empirical literature shows that deep learning frameworks outperformed traditional econometric models in applying long-term dependencies, regime shifts, and recreating the complex dynamics of markets, which are difficult to replicate with traditional approaches (Fischer & Krauss, 2018; Nguyen et al., 2024).

In this context, hybrid models that combine the advantages offered by MGARCH frameworks and deep learning architectures have been an important direction for volatility modeling (Kim & Won, 2018; Nguyen et al., 2024; Fischer & Krauss, 2018). Hybrid models combine the interpretability and strengths of traditional models with the learning and adaptability of AI, thereby producing models that will optimize volatility forecasting, enhance risk management, and better reflect market behavior in turbulent situations (García-Medina & Aguayo-Moreno, 2023; Goodell & Goutte, 2021). These models can be particularly useful during times of

financial instability or crisis, when classical models adapt more slowly to fast-evolving global market dynamics.

Against this background, the purpose of this article is to critically review and synthesize recent literature on hybrid models combining deep learning and multivariate GARCH approaches, along with theoretical insights and practical considerations in the context of financial volatility modeling. We have used an extensive and critical review of the recent methodological literature, identified the main reasons for hybrid modeling methods, and outlined some of the main methodological advances and challenges.

We have structured the paper as follows. First, we conducted an in-depth analysis of the literature in order to trace the evolution of volatility modeling, from traditional GARCH models and their multivariate variations to contemporary discussions on machine learning, deep learning, and hybrid or integrated models. The section devoted to the literature review also addressed the theoretical gaps and research motivations that underpin the shift to hybrid models. We then examined the methodological frameworks and theoretical models discussed in the literature, which extend multivariate GARCH models to deep learning methods, studying their integration logic, structural characteristics, and key issues related to their application. This was followed by an analysis of the broader implications for volatility models and the methodological and practical obstacles of financial econometrics, the best opportunities for future research (supplemented by a more in-depth analysis of the limitations), and, finally, a discussion of the main conclusions and overall contributions to academic research and financial practice.

The objective of the above material was to show the reader the steps from the fundamentals and key points of volatility modeling to recent developments in the field of hybrid learning models.

2. Literature Review

2.1. Classical GARCH and Multivariate Volatility Models

For a long time, modeling volatility in financial time series has been a major concern for econometricians and finance researchers. The emergence of the autoregressive conditional heteroskedasticity (ARCH) model (Engle, 1982) and the generalized ARCH model (GARCH) model (Bollerslev, 1986) established a robust statistical framework for measuring volatility clustering and time-varying risk in asset returns (Francq and Zakoïan, 2010; Silvennoinen and Teräsvirta, 2009). Today, ARCH and GARCH models have become indispensable in this field, both in academia and in practice, because of their empirical manageability and because they provide econometricians with a framework for testing the persistence of the volatility behavior of market variables (Bauwens et al., 2006; Goodell and Goutte, 2021).

In addition, several multivariate advances have been made on the classic GARCH, BEKK (Baba et al., 1995), and DCC (Engle, 2002) models, which aim to jointly take into account the conditional variance and covariance of different financial instruments (Bauwens et al., 2006; Silvennoinen & Teräsvirta, 2009; Likassa et al., 2025), which have significantly advanced the empirical literature on financial time series modeling. These achievements have been useful in the literature for assessing the consequences of intermarket volatility, contagion, and comovement between markets during periods of extreme financial crisis (Forbes & Rigobon, 2002; Kaminsky & Reinhart, 2000; Likassa et al., 2025). Nevertheless, classical GARCH-type processes have their limitations. They are easy to analyze due to their linear and parametric structure, but they do not provide us with adequate flexibility to take into account the peculiarities of nonlinear and high-dimensional dependencies. These peculiarities are evident in recent financial markets (Bauwens et al., 2006; Francq & Zakoïan, 2010; McNelis, 2005). In addition, the explicit addition of numerous parameters or the perturbation of the model towards higher-order dynamics can often produce an extremely large number of parameters to be evaluated, or even convergence problems (Bauwens et al, 2006; Francq & Zakoïan, 2010). In

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recent Given the continued emphasis on the significance of news, sentiment information, and high-frequency trading data for volatility forecasting (Goodell & Goutte, 2021), these are serious limitations.

2.2. Machine Learning and Deep Learning in Volatility Modeling

Machine learning and deep learning methods are better suited to processing large, high-frequency, non-linear data sets and have proven to be more effective than traditional statistics in forecasting and anomaly detection (Nguyen et al. 2024; Fischer & Krauss 2018). Due to the problems they have noticed over the past decade, we have seen growing interest in machine learning (ML) methods in finance, and more recently in deep learning (DL) methods (Goodfellow et al. 2016; Lecun et al. 2015; Fischer & Krauss 2018).

At the same time, recurrent neural networks (RNNs), and in particular long short-term memory (LSTM) networks (Hochreiter & Schmidhuber 1997) for sequential financial data, are very useful. For example, LSTMs have a special architecture that allows them to capture long-term dependencies, regime shifts, and other subtle nonlinear properties of financial data. LSTMs also have the potential to improve the accuracy of volatility forecasting and time series classification (Chen et al. 2015; Fischer & Krauss 2018). Several recent empirical articles indicate that DL models outperform traditional GARCH-type models for market shocks, sudden changes, and nonlinear dependencies (Kim & Won 2018; Fischer & Krauss 2018 ; Nguyen et al. 2024).

In the current research context, the use of Deep Learning (DL) and Long Short-Term Memory (LSTM) networks in volatility modeling is likely to be explored through two distinct categories of frameworks: univariate and multivariate frameworks.

Univariate models, such as GARCH, EGARCH, and GJR-GARCH, focus on modeling the volatility dynamics of a single financial series over time. These models estimate conditional variance (σ^2_t) based on past shocks and past volatilities, which makes it easier for them to handle persistence effects (in GARCH) and asymmetry effects (in EGARCH and GJR-GARCH). They are frequently used in these frameworks in conjunction with a deep learning architecture because they capture these nonlinear and long-term dependencies, thereby optimizing forecast accuracy.

Multivariate frameworks (e.g., BEKK-GARCH, DCC-GARCH, and cDCC-GARCH) extend this framework to more than one asset, where the model estimates a time-varying conditional covariance matrix denoted H_t. This yields dynamic correlations and volatility contagion between markets or asset classes, which is particularly important for risk diversification and contagion studies.

The context of application undoubtedly impacts the issue at hand: studies focused on cryptocurrency markets (Wang et al, 2024) frequently adopt DCC-type models in order to account for rapid co-movements and extreme volatility, while studies focused on traditional stock markets frequently use hybrid architectures, such as LSTM-GARCH, which aim to improve one-step volatility forecasts and also model structural patterns. Therefore, it is essential to distinguish between univariate and multivariate approaches, as well as between static and time-varying correlation structures (i.e., BEKK vs. DCC), in order to fully understand how deep learning complements existing econometric models in various financial contexts.

2.3. Hybrid and Integrated Modeling Approaches

Recognizing the complementary advantages of econometric and deep learning models, researchers have created hybrid econometric-deep learning frameworks that combine MGARCH models with the information processing capabilities of neural networks (Kim & Won, 2018; Fischer & Krauss, 2018; Nguyen et al., 2024). They leverage the statistical interpretability of MGARCH models and the theoretical framework they develop, adding to their MGARCH model the adaptive and data-focused learning property of deep learning models

to achieve highly promising results (García-Medina & Aguayo-Moreno, 2023). To date, examples of hybrid models include LSTM-GARCH models, parallel MGARCH-deep learning models, and MGARCH-deep learning models with sequential correction, some of which have shown improved forecasting values and stability during periods of market turmoil (Nguyen et al., 2024; Kim & Won, 2018).

Recent studies have shown that hybrid models combining deep learning and GARCH models increase the accuracy of volatility forecasts. A hybrid GARCH-LSTM volatility forecasting model was proposed by Araya et al. (2024). The GARCH-LSTM hybrid model significantly minimizes forecast errors with lower RMSE and MAE because it takes into account not only the linear structure of volatility but also nonlinear time dependence. Similarly, Han et al. (2024) suggest a time series forecasting model for non-stationary series in cryptocurrency markets using deep learning and the GARCH model. Comparative data confirmed greater accuracy and better forecasting performance in difficult, volatile, or non-stationary forecasting scenarios. These data highlight the clear value of merging econometric models and deep learning to help model and decode information about complex financial behaviors.

Among the main advantages of hybrid approaches is, first and foremost, improved brand image modeling thanks to the ability to model active nonlinear relationships and structural breaks. Fischer and Krauss (2018) and Baiuwens et al. (2006).

Secondly, they simplify the combination of alternative and exogenous data sets (Goodell & Goutte, 2021; Nguyen et al., 2024; Garcia-Medina & Aguayo-Moreno, 2023).

And finally, flexibility to respond to regime changes and periods of crisis (Garcia-Medina & Aguayo-Moreno, 2023; Wang et al., 2024).

However, there are still significant obstacles. Hybrid models are computationally intensive, require careful regularization to avoid overfitting, and may be less interpretable than traditional MGARCH models (García-Medina & Aguayo-Moreno, 2023; Goodfellow et al., 2016; Bauwens et al., 2006). The empirical literature is growing but still lacks sufficient validation across a wide range of market conditions and asset classes (Nguyen et al., 2024).

Hybrid frameworks can exhibit three primary ways of organization depending on the integration design: sequential, parallel, replacement architectures.

Each option uses the strengths of econometrics and deep learning in differing manners with different objectives, design architectures, and evaluations.

The following table summarizes the main characteristics of these hybrid strategies as reported in the literature.

Table 1: Comparative Summary of Hybrid and Integrated Modeling Approaches

Hybrid Approach	***Main Objective***	***Architecture Type***	***Main Constraint***	***Loss Function***	***Dataset / Evaluation Window***
LSTM → GARCH (Sequential)	Improve one-step-ahead volatility forecasting	Sequential (DL precedes GARCH)	Parameter stability during training	Mean Squared Error (MSE)	Stock market data, daily (2010–2020)
GARCH → LSTM (Parallel)	Capture dynamic correlations and regime shifts	Parallel (joint training)	Overfitting, model complexity	Root Mean Square Error (RMSE)	Cryptocurrency data, hourly (2016–2023)
DCC–LSTM (Replacement)	Model full covariance dynamics (Ht)	Replacement (Ht predicted by DL)	Computational cost, high dimensionality	Log-likelihood	Index-based data, daily (2015–2022)

Source: Author's synthesis based on recent studies (2022–2025).

Table 1 illustrates that hybrid methods vary in not only structural design but also methodology focus. Sequential methods are normally favored for their interpretability and temporal stability,

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while parallel architectures allow for simultaneous look-back learning yet are subject to overfitting and computational intensity. Meanwhile, replacement architectures are less restricted by the limitations of traditional models because they have more flexibility and modeling capability by learning the conditional covariance matrix H_t directly, at a financial and data cost. Overall, these distinctions highlight the inherent differences with hybrid integration across econometric and deep learning models, which can contribute to better volatility predictions and ultimately financial risk management.

In addition, beyond these structural differences, a good review should also include research that shows less definitive results.

While the majority of studies show some improvements in volatility forecasting with hybrid and deep learning-based models, we should also recognize a number of studies that report neutral or even negative results.

In some studies, hybrid models such as LSTM–GARCH or DCC–LSTM do not show a relative advantage over traditional econometric working with stable or low-volatility markets.

These findings remind us that model performance depends not only on modeling structure, but also on data quality, sample size, and hyperparameter selections.

Including these mixed results is part of methodological rigor and provides a balanced and impartial synthesis of relevant literature.

2.4. Conceptual Gaps and Research Motivation

The intersection of econometric theory and artificial intelligence in volatility modeling introduces exciting opportunities (and conceptual challenges). An entirely data-driven model can lack economic interpretability, while classical models may be too inflexible to address modern, complex financial markets (Bauwens et al., 2006; Francq & Zakoïan, 2010). The growing literature on hybrid models is helping to bridge the gap between these two extremes by leveraging the strengths of both paradigms (Nguyen et al., 2024; Kim & Won, 2018; García-Medina & Aguayo-Moreno, 2023).

This review underscores that there remains significant conceptual development and methodological integration—especially in continua with regard to validity, explainability, incorporation of alternative data, and dynamic adaptiveness (Lecun et al., 2015; Goodfellow et al., 2016; García-Medina & Aguayo-Moreno, 2023).

3. Conceptual Framework: Deep Learning Enhanced Multivariate GARCH

3.1. Rationale for Integration

The juxtaposition of deep learning (DL) techniques and multivariate GARCH (MGARCH) models is based on the complementary advantages of both methodologies. MGARCH models, such as BEKK (Baba et al., 1995) and DCC-GARCH (Engle, 2002), are often cited in the financial literature due to their theoretical foundations and interpretability in the analysis of volatility and time-varying covariances between financial series (Bauwens et al., 2006; Silvennoinen & Teräsvirta, 2009). This examination is important because these models remain a mainstay of the financial literature for treating contagion and spillover effects between markets, particularly in difficult financial conditions (Forbes & Rigobon, 2002; Likassa et al., 2025), where time-varying correlations and volatility clustering are more pronounced.

However, while MGARCH models feature time-varying correlations and conditional variances, as well as an effective modeling framework, their linear and parametric framework presents a constraint when dealing with nonlinearities, structural behavioral breaks, and multiple time-varying exogenous variables that indicate the current financial environment (Francq & Zakoïan, 2010; García-Medina & Aguayo-Moreno, 2023). On the other hand, deep learning methods, including recurrent neural networks (RNNs) and long short-term memory (LSTM) networks

(Hochreiter & Schmidhuber, 1997; Goodfellow et al., 2016; Lecun et al., 2015), provide a more robust modeling framework with nonlinear and high-dimensional relationships that normative methods may struggle to represent (Fischer & Krauss, 2018; Chen et al., 2015).
Recent empirical and conceptual research has convincingly shown that integrating deep learning (DL) into the MGARCH model can optimize forecasting performance, particularly during periods of high volatility or financial crisis (Nguyen et al., 2024; Kim & Won, 2018; García-Medina & Aguayo-Moreno, 2023).
This hybridization paves the way for models that reconcile the desired and conceptually meaningful economic interpretability of classical econometrics with the complementary and robust pattern recognition and adaptability of artificial intelligence techniques (García-Medina & Aguayo-Moreno, 2023).

3.2. Model Structure and Formulation

A conventional deep learning augmented MGARCH model is designed by applying the deep learning approach concurrently with the MGARCH model to take advantage of both approaches. Let r_t be the vector of N assets' returns at time t. The canonical BEKK-MGARCH model specifies the conditional covariance matrix H_t as follows: $H_t = C'C + A' \varepsilon_{t-1} \varepsilon_{t-1}' A + G' H_{t-1} G$ where ε_{t-1} is the innovation (error) vector at time t–1, while C, A, G are matrices of parameters (Baba et al., 1995; Bauwens et al., 2006). Once in a hybrid setting where a deep learning approach, such as an LSTM, has been implemented, you would use the deep learning model to map the historical data (returns, volatility's, and exogenous variables) to the conditional covariance matrix: $\hat{H}_t = f\_DL(r_{t-1}, ..., r_{t-p}, H_{t-1}, ..., H_{t-}q, x_{t-1}, ..., x_{t-k}; \theta)$ where f_DL is a deep learning neural net (i.e. LSTM), x_{t-i} are the exogenous variables (macroeconomic, sentiment, or alternative data), and θ are the learnable parameters from the neural network (Lecun et al., 2015; Goodfellow et al., 2016).
Three hybridization strategies are generally explained (García-Medina & Aguayo-Moreno, 2023; Nguyen et al., 2024). These include parallel hybridization: MGARCH and DL models estimated in parallel, then their results are combined (e.g., using an ensemble average) to produce the overall volatility forecast. Then, sequential hybridization of DL models is applied to model or correct the residuals of MGARCH estimates. Finally, there is complete replacement, where deep learning architectures model the entire conditional variance-covariance structure, with the MGARCH model being used only for initialization or regularization purposes.

3.3. Features and Advantages of the Hybrid Model

Hybrid deep learning–MGARCH models exhibit a few admirable features. The first characteristic is that of Nonlinear Dynamics. They are able to learn and represent nonlinear relationships, regime shifts, and long-memory effects (Fischer & Krauss, 2018; Wang et al., 2024).
Secondly, Flexible Inclusion of Covariates. They allow the inclusion of multiple exogenous and alternative data such as macroeconomic news and sentiment indices (Nguyen et al., 2024; Goodell & Goutte, 2021).
Thirdly, Robustness and Flexibility. They improve the ability to respond to structural breaks, crises, and changing market dynamics (García-Medina & Aguayo-Moreno, 2023; Wang et al., 2024).
Another important feature is the out-of-Sample Forecasting Performance. Empirical research shows increases in out-of-sample accuracy relative to classical MGARCH models, and hybrid deep learning–based approaches have demonstrated superior performance during periods of market stress (García-Medina & Aguayo-Moreno, 2023).

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Lastly, Automatic Feature Extraction. Neural networks can learn high-level features that can be extracted from the raw financial data and added to the complexity of the volatility model (Goodfellow et al., 2016).

3.4. Implementation Considerations and Challenges

Although there are some advantages, nevertheless, there are some challenges:
One of the main challenges is that of Model Complexity and Overfitting, while the flexibility of deep learning has advantages, it may lead to overfitting, which is more likely with a smaller sample, and lower levels of regularization (Fischer & Krauss, 2018).
Another critical issue concerns, Interpretability: MGARCH models are useful in terms of interpretability, while DL networks tend to follow a "black box" approach. Explainable AI is a key aspect of applications in finance (Lecun et al., 2015; Wang et al., 2024).
A further challenge is related to Computational Resources: Training and validating deep learning (DL) models can require significant computational resources (Goodfellow et al., 2016; Bauwens et al., 2006).
Another key issue that deserves attention is Validation: Despite the ability to apply various models, rigorous testing with cross-validation, along with the ability to benchmark the models against classical modeling is still required (Nguyen et al., 2024).

3.5. Summary

In conclusion, the MGARCH framework informed by Artificial Intelligence is a combination of traditional econometric modeling with contemporary Artificial Intelligence, which expands the options of flexible, more precise, and robust volatility modeling (Goodfellow et al., 2016; Nguyen et al., 2024). For the MGARCH framework informed by Artificial Intelligence to be a success, aspects around interpretability, validation, and integration of richer data sources will need to improve in the future (Lecun et al., 2015).

4. Methodology

This article proposes a conceptual framework for merging deep learning (DL) methods with multivariate GARCH models in order to enhance financial volatility modeling. The proposed approach focuses on the classic MGARCH framework (Bollerslev, 1986; Baba et al., 1995), which specifies the conditional variance-covariance matrix of asset returns \(H_t \) as follows:
$H_t = C'C + A' \varepsilon_{t-1} \varepsilon_{t-1}' A + G' H_{t-1} G$
The equation above defines the conditional covariance matrix \(H_t \) at time \(t \).
The above equation defines the conditional covariance matrix \(H_t \) at time \(t \). C, A, and G are parameter matrices; and ε_{t-1} is the vector of residuals (innovations) at time t–1.
To capture the nonlinearities and increasing complexity of financial time series, recent literature suggests extending the MGARCH model with a deep learning component, such as a long short-term memory (LSTM) architecture or a recurrent neural network (RNN) (Hochreiter & Schmidhuber, 1997; Goodfellow et al., 2016). The deep learning module is designed to map historical returns, conditional volatilities, and exogenous variables \(X_t \) to the indicators of the conditional covariance matrix as follows:
$\hat{H}_t = f\_DL(r_{t-1}, ..., r_{t-p}, H_{t-1}, ..., H_{t-x}, X_{t-1}, ..., X_{t-k} ; \theta)$
where f_DL denotes the deep learning function; \(r_{t-i} \) are lagged return vectors; H_{t-j} are lagged covariance matrices; X_{t-k} are lagged exogenous variables; and θ is the vector of network parameters in this equation. It is important to note that the integration can take on different formats:

→ Parallel hybridization: MGARCH and DL models output together as a measure to produce improved volatility estimates.

→ Sequential Corrections: Using the DL model to predict residuals (or correction) from the MGARCH model.
→ Complete replacement: the DL module directly indicates the conditional covariance structure (through the explicit architecture).
→ This hybrid structure allows the model to be more flexible when accommodating nonlinear effects, regime changes, and larger sets of covariates, resulting in more substantive volatility modeling (Nguyen et al., 2024).

In conclusion, Table 1 below presents a comparison of the primary approaches to modeling volatility that have been discussed in the literature thus far. This summary highlights the transition from classical parametric models to modern data-driven and hybrid approaches, including their respective strengths and limitations.

Table 2: Comparative Summary of Volatility Modeling Approaches

Model Type	***Main Features***	***Advantages***	***Limitations***	***Key References***
MGARCH	Multivariate, parametric	Interpretability, Theoretical Rigor	Linearity, Limited to Parametric Form	Bauwens et al. (2006); Francq & Zakoïan (2010)
Deep Learning	Nonlinear, datadriven	Flexibility, Captures Complex Patterns	Requires Large Data, "Black Box"	Goodfellow et al. (2016); Lecun et al. (2015)
Hybrid DLMGARCH	Integrates MGARCH & Deep Learning	Combines Structure &Flexibility, Robust	Computational Demands, Interpretability	Nguyen et al. (2024); Han et al. (2024)

Source: Author's own elaboration based on Bauwens et al. (2006); Francq & Zakoïan (2010); Goodfellow et al. (2016); Lecun et al. (2015); Nguyen et al. (2024); Wang et al. (2024).

In addition to the technical modeling framework, the method of this study was designed to follow a systematic literature review (SLR) process to achieve transparency and replicabiliity. The review process was conducted in accordance with PRISMA 2020, a guideline that sets a common approach to identification, screening, and selection of studies.

Data sources: The primary academic databases searched include Scopus, Web of Science, ScienceDirect, and SpringerLink. Each of these databases is known for their coverage of peer-reviewed journals in finance, econometrics, and artificial intelligence.

Search strategy: The search queries combined relevant key terms such as "volatility modeling", "GARCH", "deep learning", "hybrid models", "LSTM", and "risk management", each linked using Boolean operators (AND / OR) to capture all relevant papers published between 2015 and 2025.

Screening and inclusion criteria: Articles retrieved were screened on the articles based on title, abstract and keywords, where studies were included if (1) the study applied machine learning or deep learning techniques to volatility or risk modeling, (2) the study proposed a hybrid/integrated econometric–AI framework, and (3) the study was peer-reviewed.

Articles published in non-English languages, those published in non-academic sources, and articles that were not directly related to financial volatility were discarded.

Review Process and Bias Control: All of the articles located were separately reviewed by two independent coders, who settled any differences through discussion and consensus.

To document methodological rigor, the authors used a PRISMA flow diagram to document the inclusion/exclusion process, which highlighted the identification, screening, and inclusion of articles.

This structured approach guarantees the transparency of the method, and credibility of the findings discussed in the next sections.

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5. Discussion and Future Research Directions

The methodological advancement of combining deep learning architectures with multivariate GARCH models aims to address the growing complexities present in financial markets. The current section outlines implications, practical issues, and future research recommendations that arise from the conceptual framework outlined in this paper.

5.1. Implications for Volatility Modeling and Financial Practice

Utilizing hybrid deep learning–MGARCH models has significant ramifications for the academic research and practitioners in finance:
The first major application concerns Enhanced Volatility Forecasting Capability: The ability to capture nonlinear dependencies and switches in regimes while leveraging a large number of modeling options using exogenous variables improves the robustness and accuracy of volatility forecasts, an important aspect of risk-management, pricing derivatives, and performing stress testing.
Another important application is related to Ability to Identify Structural Breaks and Market Regimes: Compared to classical econometrics, deep learning modeling frameworks are much more flexible. This has the potential to do a much better job at identifying and understanding periods of market distress, such as a financial crisis or sudden policy change, that may be identified with classical GARCH specifications or comparable processes.
The third and perhaps most relevant application lies in More Data with Better Feature Sets: The utilization of alternatives to the traditional financial data (e.g., macroeconomic news, sentiment indices, high- speed trading data, etc.) will provide a greater ability to form a broad information set for volatility modeling enhancing out-of-sample performance.

5.2. Implications for Volatility Modeling and Financial Practice

Despite the benefits of hybrid models, we have a number of unanswered issues and questions, such as Model Interpretability: While deep learning is becoming more and more common in banking environments, it has been labeled as a "black box" and has gone through regulatory scrutiny. There is much work left to do to ensure that there is a proper level of transparency when modeling with hybrid models in formal banking and regulated financial environments. More recently developed explainable AI tools like SHAP or LIME are useful in explaining how the model generated solutions while also identifying key explaining variables.
However, Overfitting, Model validation: As a deep learning model becomes more dimensionally flexible, the risk of overfitting increases dramatically. This can be especially problematic in small sample datasets and in markets where data is "dry" more generally. Hybrid models should have a high level of out-of-sample testing and cross validation as well as regularization specifications to enhance reliability.
Another question that arises is whether, Computing Resources, Implementation: There can be significant computing resource demands on hybrid models as well as the separate challenges of running econometric models versus machine learning platforms. Banks must weigh evaluating plans to move to hybrid models versus computing costs, computing infrastructures, available technical support (code), and proficiency in skills/knowledge.
Finally, Generalizability: Hybrid models may succeed in particular cases but the generalizability of hybrid models across assets, time frames, and market conditions is a wide open development area... Through comparisons and meta-dissertations, we may learn of both success; best practices, and failures; common pitfalls of hybrid models.

5.3. Future Research Directions

The conceptual framework presented in this article opens up several avenues for future

research:
The first avenue concerns explainable and interpretable hybrid models. The aim is to develop methods that combine the predictive power of deep learning with the explanatory power of econometric modeling. This could be achieved by directly integrating interpretable machine learning methods into the modeling.
Then, transfer learning and domain adaptation. It examines whether hybrid modeling, trained on well-known liquid markets, could be transferred to less liquid or emerging markets where less data is available.
Furthermore, complex and high-frequency data. He is continuing research on how news sentiment, social media signals, limit order books, and other complex data can be systematically integrated into volatility models.
Next, real-time online learning. This allows hybrid models to be adapted to work in real time and dynamically adjust as new data becomes available. This would be very useful for applications in the field of trading and risk management.
And finally, there is comparative benchmarking. This allows for systematic comparative benchmarking of different hybrid model architectures (parallel vs. sequential, different types of neural networks) against econometric modeling with different economies.

5.4. Limitations

It is significant to be wary of the limitations of this framework both theoretically and practically. Primarily, the combination of deep learning and MGARCH models is still a nascent area of research, and many methodological issues remain unresolved, such as the selection of various architectures, parameter stability, and training methods. Secondly, while there is not particularly clear agreement on evaluation metrics for multivariate volatility modeling, there remains the issue of lacking statistical significance testing, which make evidence in empirical modes strong and not comparable to each other. Thirdly, developing hybrid models presents interpretation challenges, as deep learning models act like “black boxes,” resulting in a disconnect with outputs from models developed based on theoretical finance principles. Fourth, the design of these models gains much from the quality and availability of data as well from the technical infrastructure, which is generally an issue more relevant to emerging economies. Finally, effective implementation also relies on some level of practitioner ability in econometrics and machine learning, which might have immediate impact in what practitioners are used to.
Recognising these limitations is critical for directing future research agendas, and the ways in which hybrid models can strengthen methodological approach in financial econometrics.

6. Conclusion

In conclusion, we have provided a comprehensive conceptual framework incorporating machine learning and deep learning methodologies within the context of multivariate GARCH models for volatility modeling in finance. We have reviewed the strengths and limitations of the classical econometric methods and framed current developments in machine learning, to amplify the argument that hybrid models, integrating econometric and machine learning approaches, are suitable for tackling the complexities posed by the fast-moving markets of today.
The framework we suggested illustrates how one can combine the rigor of econometric analysis with the capacity offered by AI tools in more flexible, accurate, and robust models of volatility that are flexible enough to incorporate nonlinearities, structural breaks, as well as an evolving set of external data sources. These types of models should assist both academic researchers and practitioners in finance even if we have made little progress on generalized interpretability, validation procedures, and utilizing alternative data.

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Future research on hybrid models should focus improvements on, explainability and demonstrating utility in various iterative market set-ups. The incorporation of real-time learning, alternative data and explainable AI will be the key aspects of our advancement of state-of-the-art in financial econometrics. We hope this conceptual framework will be a helpful starting point for researchers and practitioners interested in building the next generation of volatility models.

In addition to these proposals, a key methodological concern remains largely absent from the literature. This concerns the lack of standardized multivariate performance measures and the absence of statistical significance tests, two critical shortcomings in current empirical practice. First, univariate performance measures such as MSE or RMSE are often not appropriate for multivariate volatility models, such as DCC-GARCH or BEKK-GARCH, because they are not matrix loss functions that adequately capture joint dynamics. Second, empirical claims of improved performance in the academic literature are rarely supported by formal statistical tests. Addressing these two issues in future research would improve the methodological rigor, comparability, and robustness of hybrid modeling. To summarize, we hope the framework will contribute to both academic research and industry development, and support collaboration between econometrics and artificial intelligence to lay the foundations for next-generation volatility modeling.

Références :

(1). Araya, H. T., Aduda, J., & Berhane, T. (2024). A hybrid garch and deep learning method for volatility prediction. *Journal of Applied Mathematics*, *2024*(1), 6305525.
(2). Bauwens, L., Laurent, S., & Rombouts, J. V. (2006). Multivariate GARCH models: a survey. Journal of applied econometrics, 21(1), 79-109.
(3). Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, *31*(3), 307-327.
(4). Chen, K., Zhou, Y., & Dai, F. (2015, October). A LSTM-based method for stock returns prediction: A case study of China stock market. In *2015 IEEE international conference on big data (big data)* (pp. 2823-2824). IEEE.
(5). Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of united kingrom inflation. *Econometrica*, *50*, 391-407.
(6). Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of business & economic statistics*, *20*(3), 339-350.
(7). Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric theory*, *11*(1), 122-150.
(8). Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market comovements. *The journal of Finance*, *57*(5), 2223-2261.
(9). Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European journal of operational research*, *270*(2), 654-669.
(10). Francq, C., & Zakoian, J. M. (2019). *GARCH models: structure, statistical inference and financial applications*. John Wiley & Sons.
(11). García-Medina, A., & Aguayo-Moreno, E. (2024). LSTM–GARCH hybrid model for the prediction of volatility in cryptocurrency portfolios. *Computational Economics*, *63*(4), 1511-1542.
(12). Goodell, J. W., & Goutte, S. (2021). Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. *Finance Research Letters*, *38*, 101625.

(13). Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning* (Vol. 1, No. 2). Cambridge: MIT press.
(14). Han, H., Liu, Z., Barrios Barrios, M., Li, J., Zeng, Z., Sarhan, N., & Awwad, E. M. (2024). Time series forecasting model for non-stationary series pattern extraction using deep learning and GARCH modeling. *Journal of Cloud Computing*, *13*(1), 2.
(15). Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*(8), 1735-1780.
(16). Kaminsky, G. L., & Reinhart, C. M. (2000). On crises, contagion, and confusion. *Journal of international Economics*, *51*(1), 145-168.
(17). Kim, H. Y., & Won, C. H. (2018). Forecasting the volatility of stock price index: A hybrid model integrating LSTM with multiple GARCH-type models. *Expert Systems with Applications*, *103*, 25-37.
(18). LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature*, *521*(7553), 436-444.
(19). Likassa, H. T., Chen, D. G., Nadarajah, S., Sema, M., Chen, J. K., Temesgen, S., & Gotu, B. (2025). A Multivariate GARCH Model with Time-Varying Correlations: What Do Inflation Data Show in Ethiopia?. *Computational Economics*, 1-33.
(20). McNelis, P. D. (2005). *Neural networks in finance: gaining predictive edge in the market*. Academic Press.
(21). Nguyen, H. T., Nguyen, H., & Tran, M. N. (2024). Deep learning enhanced volatility modeling with covariates. *Finance Research Letters*, *69*, 106145.
(22). Silvennoinen, A., & Teräsvirta, T. (2009). Multivariate GARCH models. In *Handbook of financial time series* (pp. 201-229). Berlin, Heidelberg: Springer Berlin Heidelberg.