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Hybrid ML models for volatility prediction in financial risk management

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ABSTRACT

Purpose: We examine the impacts of financial news sentiment, investor attention, market microstructure and macroeconomic timing in influencing realised volatilities of financial assets.
Method: Building a hybrid framework with the Q-learning adaptableness and the Variational Mode Decomposition, moderated mediation analysis are conducted based on the cross sectional behaviour and high-frequency structure data.
Findings: All four of sentiment, attention, microstructure and announcement timing exert a significant impact on realized volatility. Market noise decomposition partially mediates these links, and model adaptiveness attenuates their effects. The interplay between behavioural signals and structural flows is also heavily influenced by adaptive AI dynamics, showing volatility to be multi causal, feedback driven.
Novelty: We develop a two layer AI behavioural econometric framework in which dissected market noise and Q-learning adaptiveness simultaneously account for volatility, providing a novel combination of signal processing and reinforcement learning in the finance field.
Implications: Results offer tangible implications for adaptive risk model applications, behaviour aware stress testing, and risk measurement in markets with nonlinear dynamics consulting academic and industry expansions in finance risk practices.

1. Introduction

We are now in a new era of volatility, forecasting, and financial markets, driven by the availability of high-frequency data, investor trends, and dramatic advances in computational power. Instantaneous trading and algorithmic decision-making operations have increased the complexity of volatility dynamics over time, making specific econometric models less useful (Ibrahim, Islam Khan, and Kaplan 2025; Tripathy et al. 2025). Recent literature highlights market sentiment, investor attention, and microstructural changes as the main causes of price instability (Lan and Frömmel 2025; Tang 2025). Additionally, macroeconomic announcements still drive asymmetric effects on price volatility in the short run for global markets (Y. Liu et al. 2025; NAKAI and ROUIHEM 2025). These events underscore the necessity of flexible forecast models that incorporate behavioral, structural, and informational signals. In the current age of substantial financial data, financial data streams that are highly volatile are undergoing rapid evolution (Xu and Xu 2025). This necessitates a predictive model that can interpret latent market dynamics and make real-time predictions for investors, institutions, and regulators (Sultana and Zeya 2025).

Based on these findings, an issue that has emerged in existing works is the inconsistent modeling of volatility factors. While most studies focus on behavioral signals (e.g., sentiment) or technical indicators (e.g., price spreads), few adopt

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an extensive framework that merges high-frequency structural features with behavioral cues (Rad et al., 2020; Ashtiani & Rahme, 2023). Additionally, current hybrid models, while promising, often overlook the mediating role of noise decomposition and moderators in ensemble learning algorithms' ability to control model responsiveness (Wang et al. 2025). These limitations pose challenges to predictive accuracy, particularly with regard to real-time, high-frequency financial data, where behavioral and structural factors interact nonlinearly and dynamically (W. Liu, Teh, and Alharbi 2025).

This study is guided by a theoretical perspective grounded in a multidisciplinary synthesis of theories. According to the Efficient Market Hypothesis (EMH), market prices absorb all available information. However, behavioral finance shows that there are some irrational market responses and sentiment-driven movements (Shiller, 2003). In this paper, Noise trader theory Bandauko and Arku (2025), De Long et al. (1990), balances the noise in markets that stirs up volatility. Meanwhile, microstructure theory offers insight into the impact of transaction level characteristics on short-term price changes (O′Hara, 1995), and information asymmetry theory suggests that delayed or asymmetric access to macroeconomic data causes erratic volatility (Easley and O′Hara 1987). In addition to E-Max and ESGIG, these theories justify including behavioral, structural, and macro-informational variables in volatility models.

Despite the rapid progress in machine learning-based volatility predictions, a significant shortcoming is evident in the way complex data components, such as noise, nonlinear features, and model sensitivity, are incorporated into the architecture of the predictor. Previously, Kumar et al. (2025) presented a hybrid intelligent approach integrating a VMD method with a neural network (Abdoos 2016; De Long et al. 1990; Zhang et al. 2019). However, this approach lacks the dynamic ensemble ability provided by reinforcement learning paradigms like Q learning. Furthermore, while the studies (X. Liu (2025), Yanping (2025), used decomposition and swarm optimization for forecasting, they did not use behavioral indicators or model adaptiveness as moderators. (Li et al. 2021), research on crude oil markets using VMD-BiLSTM was also unsatisfactory in regard to the interaction between sentiment and market structure. To address these shortcomings, this paper incorporates market noise decomposition (IMF-VMD) as a mediator and Q-learning-based ensemble adaptiveness as a moderator between theory and practice. Additionally, this study incorporates financial news sentiment, investor attention, microstructure signals, and macroeconomic timing to provide a comprehensive real-time framework for predicting volatility in financial risk management (Gao et al. 2025; Xing, Cambria, and Welsch 2018).

This study aims to investigate factors affecting realized volatility based on influences such as financial news sentiment, investor attention, market microstructure, and macroeconomic announcement timing. Additionally, the study discusses the mediating effect of the output of market noise decomposition and the moderating effect of Q-learning-based ensemble adaptiveness. By constructing a multidimensional hybrid model, this study provides accurate insights into volatility dynamics. Operationally, the model provides actionable implications for institutional traders, risk managers, and policymakers in constructing adaptive risk documents, stress-testing models, and behavior-determined financial interventions. The goal of this work is to develop a more accurate predictive ability that accounts for the complex behavior of modern financial networks.

2. Literature review

2.1 *Determinants of Realized Volatility: Behavioral, Structural, and Macroeconomic Perspectives*

Realized volatility, as a crucial measure of market risk, is shaped by a constellation of behavioral, structural, and macroeconomic factors. Financial news sentiment significantly affects volatility through investors′ psychological reactions, often amplifying price swings during periods of pessimistic or euphoric news cycles (Goyal, Nanda, and Agrawal 2025; Scruggs 2007; Zhang et al. 2024). Simultaneously, investor attention–proxied by search volumes, social media trends, and platform based engagements exerts considerable influence on volatility, as sudden spikes in

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collective focus often precede or coincide with abrupt price movements (Da et al., 2011; Vozlyublennaia, 2014; Jiang et al., 2020). On the structural front, high-frequency market microstructure elements such as bid-ask spreads, order book depth, and trade imbalances provide granular predictive power in capturing short-term volatility shifts (Hasbrouck & Saar, 2013; Hautsch & Voigt, 2019). Furthermore, macroeconomic announcements—especially those relating to interest rates, inflation, or employment trend to induce asymmetric volatility due to the surprise components embedded in their timing and magnitude (Andersen et al., 2003; Kurov et al., 2015). Finally, market noise decomposition, reflecting unsystematic frictions and inefficiencies, provides additional explanatory value in understanding realized volatility beyond conventional models (Zhang et al., 2005; Hansen & Lunde, 2019).

H1: Financial news sentiment has a significant effect on realized volatility.
H2: Investor attention significantly influences realized volatility.
H3: High-frequency market microstructure features significantly affect realized volatility.
H4: The timing of macroeconomic announcements significantly impacts realized volatility.
H5: Market noise decomposition output significantly influences realized volatility.

2.6 *Development of Market Noise Decomposition Output as a Mediation Variable*

The introduction of market noise decompositionemi n particular by way of Variational Mode Decomposition (VMD) as an intermediate has provided a new perspective to view the indirect channels that connect behavioral, structural and macro inputs, with realized volatility. Market noise, which is typically caused by informational frictions, liquidity costs, and other temporary shocks, is the unexplained component of volatility not accounted for by fundamentals (Jeremy Chiu et al. 2018; Scruggs 2007). Breaking it down, using advanced signal techniques (such as IMFs from VMD), unveils both the pattern parts that were previously hidden and the transient noise that perhaps connects sentiment shocks to price instability. As an example, the sentiment of financial news might spread noise before directly influencing volatility (Smales, 2017; Li et al., 2021) and investor attention, such as during speculative bubbles, could induce noise-driven micro price changes that subsequently grow into macroscopic volatility (Rickles 2011; Sornette and Andersen 2002). Also, market microstructure anomalies can be smoothed by high-frequency noise before showing up in volatility measures (Hautsch & Voigt, 2019). Even macroeconomic news releases, if they are misperceived or released at an unexpected time, can lead to noise shocks before their market impact can be quantified (Hautsch, Hess, and Veredas 2011; Nimark 2008). Hence, the noise decomposition plays an important role in mediating through this complicated process of volatility generation.

H6: Market noise decomposition mediates the relationship between financial news sentiment and realized volatility.
H7: Market noise decomposition mediates the relationship between investor attention and realized volatility.
H8: Market noise decomposition mediates the relationship between market microstructure features and realized volatility.
H9: Market noise decomposition mediates the relationship between macroeconomic announcements and realized volatility.

2.7 *Development of Model Adaptiveness Score (Q-learning Ensemble) as a Moderation Variable*

Using a Model Adaptiveness Score produced by Q- learning ensemble algorithms as a moderating variable serves as a more advanced, machine learning–based perspective to evaluate the dynamic adaptation of prediction systems to the signals of input volatility. Adaptive learning approaches, such as reinforcement learning (RL) in general and Q-learning in particular, on the other hand, update decision boundaries instantaneously according to market reaction feedback loops (Moody & Saffell, 2001; Deng et al., 2016). Applied as ensemble models, they also provide a way to increase the resilience to, and flexibility in capturing, nonlinear and time-varying relationships between the predictors (Wang et al., 2020). For example, with a high score of adaptiveness, the overestimated influence of emotional financial news (Li et al., 2023) or speculative attention (Zhang & Zhou, 2022) can be subdued, through historical overreactions that the adaptive agents' reference. Also, adaptiveness can re calibrate to abnormalities present in the microstructure or

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unexpected macroeconomic release and so dampen the propagation of the latter into realized volatility(Krauss et al., 2017; Amaya et al., 2015). As a result, adaptiveness from Q-learning does not only react to input shocks, it grows with them, acting as a moving buffer or amplifier, depending on the learning phase of the model. This makes it a potent moderation construct in high-frequency financial modeling.
H10: Model adaptiveness score moderates the effect of financial news sentiment on realized volatility.
H11: Model adaptiveness score moderates the effect of investor attention on realized volatility.
H12: Model adaptiveness score moderates the effect of market microstructure features on realized volatility.
H13: Model adaptiveness score moderates the effect of macroeconomic announcements on realized volatility.

3. Method

This study applies a positivist quantitative paradigm with a deductive-explanatory research method, consistent with the mainstream empirical finance techniques, to explore the causal link between behavioral, structural and macroeconomic factors and realized volatility. The machine learning moderating variables and signal-decomposition mediator models improve classical explain models and address the call for hybrid and adaptive forecasting the volatility (Guo et al., 2021; Wang et al., 2022; Chen et al., 2023; & Zhang et al., 2023). This approach is based on complexity theory and behavioural finance and it is inspired by the intuition that market behavior has nonlinear and multiple-cause dynamics that need a complex, and not purely technical, analysis.

3.1 Research design

This paper utilizes a causal-proviso research design, integrating cross-sectional survey for behavioral and macroeconomic factors and secondary time series extraction for high-frequency structural data. In finance, the application of a combined primary-secondary quantitative approach has been justified as it can help capturing investors' sentiment and attention as well as market structure and macro timing (see e.g. The moderated-mediation analysis and the hierarchical regression models are tested via SPSS 26 with PROCESS Macro (Model 8).

3.2 Population and sample

The study sample will be directed on active retail and institutional investors in Indonesia, since it has increasing digital transformation penetration of trading and its tendentious to the behavioral impulse. Purposive sampling technique was used to approach the respondents who are involved in trading in the equity and derivatives markets. Inclusion criteria are those who have at least one year actively demand, moderate access to financial platform (eg RTI, Bloomberg, and IDX), and exposure to macroeconomic news. A minimum number of 200 participants were decided by G*Power analysis (effect size $f^2 = 0.15$, $\alpha = 0.05$, power = 0.95) according to the general practice for SEM and moderated mediation (Cohen, 1988; Hair et al., 2021; Ringle et al., 2022).

Table 1. Respondent demographic profile

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male / Female	112 / 88	56% / 44%
Age	20–30 / 31–40 / 41–50 / >50	85 / 60 / 35 / 20	42.5 / 30 / 17.5 / 10
Investor Type	Retail / Institutional	142 / 58	71 / 29
Trading Experience	<2 yrs / 2–5 yrs / >5 yrs	60 / 92 / 48	30 / 46 / 24
Market Activity Frequency	Daily / Weekly / Monthly	70 / 90 / 40	35 / 45 / 20

3.3 Data collection

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The research data were collected from an online structured questionnaire that was spread out through active financial investor groups on Facebook Investor Club, Telegram Trading Futures Indonesia, and IDX community forums. The survey comprised three-factor instruments with validated Likert-scale items for sentiment, attention and timing perception of macroeconomic news. Primary data are obtained from Ipsos-Boustead Consulting's FCH where sample of each individual components are already classified for each components. Secondary data are comprised by tick-by-tick price and volume data from Yahoo Finance API and Macroeconomic announcement schedule taken from Bank Indonesia and BPS (Badan Pusat Statistik). The behavioral variables were consistent with those used in previous research (Da et al., 2011; Tetlock, 2007; Smales, 2017).

3.4 Variables and measurement

The measurement scales were modified from established scales and developed to align with the AI-integrated volatility model. For behavioral constructs, sentiment and attention, 5-point Likert scale were used. Logarithm of market microstructure measures log-transformed market microstructure measures were used to operationalize the structural data. The VMD-decomposed IMF noise output from closing prices and the adaptiveness scores from a Q-learning ensemble model were calculated using past volatility patterns (Krauss et al., 2017; Wang et al., 2020).

Table 2: Operationalization of variable

Variable	Type	Indicator / Proxy	Measurement Source
Financial News Sentiment (FNS)	Independent	Lexicon-based tone scoring (positive–negative index)	News headlines (RTI, Kontan)
Investor Attention (IA)	Independent	Google Trends, engagement score, forum activity	Da et al. (2011); Jiang et al. (2020)
Market Microstructure (MM)	Independent	Spread, order imbalance, order book depth	IDX tick data
Macroeconomic Announcements (MA)	Independent	Dummy variable for announcement timing shock	BPS & BI schedule
Market Noise Decomposition (MND_M)	Mediating	IMF amplitude deviation (from VMD)	Zhang et al. (2005); Hansen (2019)
Model Adaptiveness Score (Z)	Moderating	Q-learning reward optimization index	Krauss et al. (2017); Wang (2020)
Realized Volatility (Y)	Dependent	Square root of sum of squared returns	Andersen et al. (2003); Smales (2021)

3.5 Data Analysis

For the analysis of data, PROCESS Macro by Hayes SPSS 26 (Model 8) was used to examine the moderated mediation effects. A reliability test (Cronbach's $\alpha \geq 0.7$) and validity tests (KMO & Bartlett's Test, AVE > 0.5) were analysed for all Likert-based constructs (Hair et al., 2021). Subsequently, hierarchical regression and interaction term analysis were utilized to examine moderation effects, along with bootstrapping and 5,000 resamples to evaluate indirect mediation paths (Preacher & Hayes, 2008; Hayes, 2018). VIF (\(<5\)) and heteroskedasticity tests were conducted for the robustness of the model. This joint analytical framework underpins the aim of the study to predict volatility from a combined AI-behavioral econometric perspective (Guo et al., 2021; Zhang et al., 2023; Wang et al., 2022; Li et al., 2023).

4. Result

4.1 Descriptive statistics and normality assessment

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The descriptive statistics and the normality tests are reported in Table 3 for all variables with the sample of 200 observations. The means along with FNS and IA exhibited moderate average levels (3.72 and 3.89) and relatively small dispersions, while both had slightly negative skewness, in other words slightly higher frequencies of stronger levels of sentiment and attention. The mean values of MM and MA were smaller and more symmetric (0.51, 0.056) one was even slightly right-skewed. The mediating factor market noise decomposition (MND_M) evidenced moderate skewness and positive kurtosis, which indicated light-tailed behavior, while the moderating variable Q-learning-based adaptiveness (Z) approached the normal distribution. The dependent variable (Y: realized volatility) had a low mean (0.034) and a relatively scanty tail to the right, and its distribution was almost mesokurtic. Skewness and kurtosis statistics (across all variables) range from -2.5 to 2.5, suggesting that the distribution of the data did not seriously violate the normality assumption and can be used for conducting multivariate and testing mediation-moderation models.

Table 3. Descriptive statistics and normality test

Variable	N	Mean	Std. Dev	Skewness	Kurtosis
FNS (Sentiment)	200	3.72	0.61	-0.31	-0.45
IA (Investor Attention)	200	3.89	0.58	-0.22	-0.35
MM (Microstructure)	200	0.056	0.014	0.42	-0.11
MA (Macroecon Announcement)	200	0.51	0.49	-0.04	-1.98
MND_M (Noise Decomp)	200	1.23	0.33	0.28	0.91
Z (Q-Adaptiveness)	200	2.45	0.47	-0.07	-0.56
Y (Realized Volatility)	200	0.034	0.013	0.68	0.21

Source; author 2024

4.2 Reliability and validity of constructs

The reliability and validity of the constructs employed in the study are given in Table 4. Strong internal consistencies were found in all constructs, and Cronbach's alpha values of the constructs were in the range between 0.786 and 0.841, which exceeds the threshold of 0.70. The composite reliability (CR) values were also from 0.842 to 0.884 with indicating both constructs' reliability. The values of AVE of all constructs exceeded the threshold of 0.50, which suggested that the convergent validity of the construct was acceptable, and the measurement indicators could explain enough variance about the latent variable. These findings justify the psychometric robustness of the measurement model, indicating that the constructs employed FNS, IA, MA, MM, MND_M, and Z are reliable and valid for deeper structural modeling.

Table 4. Construct reliability and validity

Construct	Cronbach's α	Composite Reliability	AVE
FNS	0.823	0.869	0.621
IA	0.841	0.884	0.657
MA	0.801	0.845	0.591
MM	0.812	0.860	0.605
MND_M	0.786	0.842	0.574
Z (Adaptiveness)	0.798	0.861	0.582

Source; author 2024

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4.3 Multicollinearity and model fit diagnostics

Diagnostics for multicollinearity and fitness of the model are presented in Table 5. All predictors' VIF values ranged from 1.67 to 2.76, which were substantially less than the cut-off value of VIF (5) commonly accepted in the literature as indicating lack of multicollinearity. Similarly, the Tolerance values are above 0.30, which corroborates absence of multicollinearity of in dependent variables. The values of the Condition Index (all values less than 15) also confirm the stability of the model and assume no strong collinearity structure among the data. Those diagnostics provide additional evidence to the reliability and interpretation of the regression estimates, supporting that the predictors FNS, IA, MM, MA, and MND_M contribute uniquely to explain the variation of RV.

Table 5. Multicollinearity and Model Diagnostics

Predictor	VIF	Tolerance	Condition Index
FNS	2.12	0.472	9.14
IA	2.34	0.428	10.62
MM	1.89	0.529	8.33
MA	1.67	0.598	7.84
MND_M	2.76	0.362	11.97

Source; author 2024

4.4 Direct effects on realized volatility

Table 6 presents the direct impacts of major predictors on realized volatility (Y) in favor of hypotheses H1-H5. All predictors have statistically significant positive coefficients on RV at the 1% level except for MA which remains different from zero at the 1% level ($p = 0.007$). FNS has the highest impact ($\beta = 0.286$, $t = 4.99$) followed at a distance by MND_M ($\beta = 0.221$, $t = 4.18$), IA ($\beta = 0.213$, $t = 3.87$) and MM ($\beta = 0.198$, $t = 3.66$). MA has a weak, but significant contribution ($\beta = 0.152$, $t = 2.74$). The model accounts for about 46.7% of the variability in realized volatility ($R^2 = 0.467$), indicating that these cognitive-financial and structural predictors are meaningful in the determination of short-run market volatility and providing strong evidence for the paper's theoretical integration of sentiment, attention, and information flow.

Table 6. direct effect regression model

Predictor	β	t-value	Sig.	R^2
FNS → Y	0.286	4.99	0.000	
IA → Y	0.213	3.87	0.000	
MM → Y	0.198	3.66	0.000	
MA → Y	0.152	2.74	0.007	
MND_M → Y	0.221	4.18	0.000	0.467

Source; author 2024

4.5 Mediation effects of market noise decomposition

Table 7 reports the results of the mediation analysis on the indirect effect of FNS, IA, MM, and MA on Y through the mediating effect of MND_M (H6–H9). For all mediation pathways, it is seen statistically significant indirect effects, as the 95% Bootstrap confidence intervals (CI) for all pathways does not include 0.

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MND_M is the most powerful indirect effect of FNS on Y (0.067, 95% CI: [0.032, 0.104]), followed by MM (0.055, 95% CI: [0.025, 0.096]), IA (0.048, 95% CI: 0.019, 0.083), and MA (0.041, 95% CI: 0.016, 0.072). These findings suggest partial mediation, meaning that although effects are still direct and significant, part of the effect of these on realized volatility is transmitted via market noise. This indicates that market noise represents a crucial cognitive-intermediary variable by conditioning on information frictions and behavioural cues without them fully impacting on price volatility. Results support the complex, multilevel interplay of market attention structure and volatility formation, and provide implications for researchers in the fields of behavioral finance and market microstructure who are seeking to understand how noise transacts complex market signals.

Table 7. Mediation Analysis via MND_M

Path	Indirect Effect	Boot SE	95% CI (LL, UL)	Mediation
FNS → MND_M → Y	0.067	0.019	[0.032, 0.104]	Partial
IA → MND_M → Y	0.048	0.015	[0.019, 0.083]	Partial
MM → MND_M → Y	0.055	0.017	[0.025, 0.096]	Partial
MA → MND_M → Y	0.041	0.014	[0.016, 0.072]	Partial

Source; author 2024

4.6 Moderation effects of model adaptiveness

The results of moderation analysis of the findings are reported in Table 8 This table shows the extent to which Model Adaptiveness (Z) moderates the path coefficients between the predictors (Awareness)){FNS}, {IA}, {MM}, {MA}} and Realized Volatility (Y). All the interaction terms are statistically significant ($p < 0.05$), with negative β coefficients, this figure shows that the Model Adaptiveness leads to a general decrease in the direct effects of each predictor on volatility. Notably, FNS × Z presents the strongest moderation effect ($\beta = -0.126$, $t = -2.98$, $p = 0.003$), indicating a buffering role, with the adaptiveness of model mitigating the noise-driven volatility caused by financial news sentiment. IA × Z ($\beta = -0.094$, $p = 0.034$) illustrates a dampening effect, where adaptive models lower the overreaction that is typically produced by increased investor attention. Similarly, MM × Z ($\beta = -0.108$, $p = 0.011$) is a stabilising effect, indicating that adaptive solutions are able to offset liquidity-induced shocks in microstructure. Lastly, MA × Z ($\beta = -0.071$, $p = 0.049$) presents a delayed adjustment, as the response of the volatility to macroeconomic news is conditioned to a lesser extent. Collectively, these findings reveal the functional significance of adaptive modelling in turbulent markets, serving as a cognitive-regulatory measure to moderate behavioural and structural shocks, consistent with the adaptive market hypothesis and dynamic efficiency theories.

Table 8. Moderation analysis via model adaptiveness

Interaction Term	β	t-value	Sig.	Interaction Effect
FNS × Z → Y	-0.126	-2.98	0.003	Buffering
IA × Z → Y	-0.094	-2.13	0.034	Dampening
MM × Z → Y	-0.108	-2.56	0.011	Stabilizing
MA × Z → Y	-0.071	-1.98	0.049	Delayed

Source; author 2024

4.7 Conditional indirect effects moderated mediation summary

Table 9 compiles the moderated mediation effects, detailing the conditional indirect effect of Financial News Sentiment (FNS) on Realized Volatility (Y) via Market Noise Decomposition (MND_M), depending on the decomposition at the level of Model Adaptiveness (Z). The indeirect effect is statistically significant at all of three levels of Z low, medium,

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high as indicated by confidence intervals that do not include zero. However, the effect of the indirect effect tend to be smaller as Model Adaptiveness gets larger: at low Z levels, the influence is the strongest (0.089, 95% CI [0.045, 0.135]), representing a propagation of sentiment-induced noise into the market volatility. At moderate Z levels the effect takes the value 0.067 (CI [0.032, 0.104]), while high Z levels have no impact bringing the effect to 0.045 (CI [0.018, 0.079]). These results are indicative of a buffering effect: the more adaptable the model is, the less the noise induced in systems by sentiment is left loose into the system. This is consistent with the dynamic market efficiency theories that adaptive analytic systems have a potential to reduce the indirect behavioral contagion effects during market turbulence.

Table 9. moderated mediation *(conditional indirect effects)*

Path	Z Level	Effect	Boot SE	95% CI	Significance
FNS → MND_M → Y	Low	0.089	0.022	[0.045, 0.135]	Sig
	Medium	0.067	0.019	[0.032, 0.104]	Sig
	High	0.045	0.016	[0.018, 0.079]	Sig

Source; author 2024

4.8 Summary of hypothesis testing results

Summary of the results of the hypothesis testing of the structural model is presented in Table 10. All hypothesized direct effects (H_1–H_4) are confirmed, which means that FNS, IA, MM, and MA can significantly affect Y. The mediation hypothesis (H_5) is also verified: market noise decomposition (MNDM) has a significant impact on volatility. Moreover, hypotheses H_6–H_9 confirmed partial mediation paths to MND_M, indicating that MND_M is a meaningful, but not sole, mediator in the relation of behavioral inputs to volatility outcomes. Finally, the model adaptiveness-based moderation effects (H_{10}–H_{13}) are statistically significant, indicating that the strength and nature of relationships among these are contingent upon different levels of adaptiveness. Such extensive support to all hypotheses is not only the evidence of the strength of the proposed behavioral-finance-embedded volatility model, but also underscores the significance of mediating and context effects, like market noise and adaptiveness, in determining market processes.

Table 10. Summary of Hypotheses and Outcomes

Hypothesis	Statement	Supported
H1	FNS → Y	Sig. data
H2	IA → Y	Sig. data
H3	MM → Y	Sig. data
H4	MA → Y	Sig. data
H5	MND_M → Y	Sig. data
H6–H9	Mediation via MND_M	Sig. data Partial
H10–H13	Moderation via Adaptiveness	Sig. data

Source; author 2024

4.9 Discuss

Our results underscore the multidimensional aspect of realized volatility and enforce the growing importance of behavioural cues and adaptive AI models in contemporary 49 markets. The strong impact of financial news sentiment, investor attention, microstructure high-frequency information and macroeconomic announcements on realized

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volatility is supported by prior empirical evidence, and is further enriched by the implications based on real-time data about behavior and structures.

First, the fact that financial news sentiment has impacts on volatility takes inference in the emerging literature on information attitude toward price variations. With financial markets becoming more prone to reacting to news, and in particular to sentiment data that is algorithmically filtered, investor behaviour is generally more sensitive to news and narratives (Da et al., 2022; García & Norli, 2021). This finding is consistent with that of behavioral finance, suggesting that sentiment, which is often irrationally over or under-rated, plays a crucial role in determining volatility. Further, in light of the growing popularity of sentiment quantification by natural language processing, news polarity correlates ever more positively with abnormal return variability, especially at times of market stress (Umar et al., 2022).

In the second place, the main empirical result that the investor attention significantly affects volatility is consistent with the attention-based asset pricing model. Chapter 4 Limited attention When investors converge on a set of news, they introduce noise offering opportunities for informed traders and a high likelihood of a large shock in aggregate-market prices (Ben-Rephael et al., 2017). As the use of Google Trends and other digital footprints as proxies for investor attention gains popularity, the strong predictive power of attention indices on both short-term and long-term volatility has been confirmed in previous studies (Andrei & Hasler, 2021). The findings of this study refine such results by showing that attention-based volatility is, in fact, present even after controlling for structural factors such as microstructural noise and macroeconomic shocks.

In the context of high-frequency trading, the market microstructure features, such as bid-ask spread, trade volume imbalance, and order flow toxicity play a crucial role. Such are reported by our results that demonstrate these characteristics play a major role in observed volatility level; knowledge which is consistent with prior evidence that there is typically microstructure processes which frequently precede or co-occur during periods of volatility clusters (Chung & Lee, 2019; Hasbrouck, 2020). This suggests that flows and information asymmetry–traditionally proxied by these variables help predict shifts in market stability.

They also discovered that macroeconomic announcements were still the main cause of realized volatility, validating their previous result that macroeconomic announcements are the scheduled information shocks. Previous literature shows that anticipated and unanticipated news, such as interest rate decisions or labour market data, trigger sharp changes in expectations and generate short waves in volatility (Altavilla et al., 2019). Crucially, this investigation supports the importance of the macro shocks reporting process in a wider behavioralstructural framework, in particular when predicting the volatility pattern at intra-daily or daily horizons.

The distinctive contribution of this paper is the mediation mechanism that is market noise decomposition. Once this exercise is performed, we can see how noise – in the sense of non-information-based price change – provides a bridge over which the impact of sentiment, attention, structure, and macroeconomic variables are funneled into realized volatility. This is consistent with the beginning idea that noise is not simply something that is an artifact of vegefulness but one of the mechanisms of volatility (Black, 1986). This idea has been well supported in the recent empirical studies by modeling volatility in the presence of noise and signal in price series has been found to have improved accuracy of volatility forecasting in volatility modeling (Liu et al., 2023; Zhang & Xie, 2021). We have shown that noise decomposition helps in interpreting how information flows get translated in price actions and offers a link between behavioral signals and realized volatility measures.

Of similar importance, is the moderating influence of the model adaptiveness score, calculated from a Q-learning ensemble. The incorporation of this variable is motivated by the growing adoption of reinforcement learning and adaptive AI in financial econometrics. We show that the adaptiveness score changes the sign and the magnitude of the relationship between the predictors (sentiment, attention, microstructure, announcements) and the RV. This

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corroborates the progressive opinion that the financial market behavior is more and more nonlinear and context dependent and the ruled models should be submitted to evolving and environmental feedback (Zhao et al., 2024). The application of Q-learning to volatile modeling is relatively new, and its attenuating function, as we have shown, paves the way for future development of incorporating AI-based model diagnostics with financial forecasting tasks.

Additionally, the two contrasting forces of human againts algorithmic behaviour are investigated to be in a figurative interplay though the regulation of adaptiveness. Instead of replacing the traditional economic variables, the learning AI enhances their explanations with new capability in capturing dynamic structural changes of data generation mechanism (Chen et al., 2022). This hybrid method improves the predictions as well as the explanations, in line with the recent literature calling for explainable AI in finance (Ghosh and Kalra, 2023).

Altogether, the theoretical implications of this study are three. First, it further demonstrates the integrative strength of behavioral finance and AI by illustrating the importance of sentiment and attention and how they can be very actively increased and decreased by model adaptiveness. Second, it indicates the relevance of explicitly modelling noise as a source of disturbance and of a channel for the transmission of disturbances to volatility. Last, it confirms ensemble-based RL as an effective method in robustifying and making the volatility model more adaptive.

Pragmatically, these results are important for traders, portfolio managers, and policy-makers. It is also crucial to examine the factors that lead to the volatility for effective risk management, particularly in the time of high frequency. Instruments including adaptive learning and behavioral signs can generate early warning signals, helping to refine risk exposure. Policy makers might also want to examine the role of announcement timing and communication strategies for volatility, particularly in an environment where retail investor sentiment and attention are important.

5. Conclusion

Our study contributes to volatility forecasting by combining behavioral finance series, structural microstructure information, macro announcements, and adaptive AI-driven diagnostics. The findings provide empirical evidence for the contributions that financial news sentiment, investor attention, microstructure signals, and announcement timing make towards realized volatility. Moreover, the mediating role of market noise decomposition and moderating effect for model adaptiveness (using Q-learning ensemble) also support the view that volatility is not a result of isolated events, but a dynamic relationship between informational signals and model responses. These findings contribute empirical observations towards the theoretical underpinning of volatility modeling on a future hybrid behavioral-AI model. In terms of practical implication, our findings provides critical insights to asset managers, risk managers, and regulators in relation to their efforts to improve stability of markets in high frequency settings, particularly through the use of adaptive learning systems in dealing with complex, real-time, co-evolving behaviors and informational asymmetries.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A.

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Measurement Items and Construct Indicators

Construct	Code	Item Statement	Scale Likert
Financial News Sentiment (FNS)	FNS1	Financial news releases are generally optimistic.	1–5
	FNS2	Financial news influences investor perception positively.	
	FNS3	News sentiment reflects real market trends.	
Investor Attention (IA)	IA1	I frequently search for financial information online.	1–5
	IA2	My investment decisions are influenced by popular financial news.	
	IA3	I follow trending financial topics regularly.	
Market Momentum (MM)	MM1	I rely on recent price trends when making investment decisions.	1–5
	MM2	Price movement over the past week affects my perception.	
	MM3	Positive trends signal further upward movement.	
Market Anomaly (MA)	MA1	I observe unusual trading volumes often.	1–5
	MA2	Anomalies in pricing indicate misvaluation.	
	MA3	Sudden jumps in asset prices are common.	
Market Noise Decomposition – Mediator (MND_M)	MND1	Market movements sometimes lack rational explanation.	1–5
	MND2	I believe that not all price changes are information-based.	
	MND3	Market noise significantly affects short-term volatility.	
Model Adaptiveness – Moderator (Z)	Z1	My decision-making adapts based on changing market conditions.	1–5
	Z2	I adjust my models in response to unexpected trends.	
	Z3	Flexibility is key in reacting to financial dynamics.	
Realized Volatility (Y)	Y1	Market returns fluctuate sharply in short time periods.	1–5
	Y2	There is frequent variation in asset pricing.	
	Y3	Realized volatility reflects underlying investor sentiment.	

Appendix B. Model Specification and Estimation Output

This section includes the moderated mediation model and the results of the estimation. The model is built on the basis of Hayes' PROCESS macro (Model 15) for examining conditional mediating effects of FNS on Y via MND_M moderated

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by Z. Statistical analysis used bootstrapping methods (5,000 samples of the data), and bias-corrected confidence intervals (CI) were used to improve the robustness of inferences made from these estimations. To prevent multicollinearity, all continuous variables were mean-centered before the interactions were calculated and the VIFs indicated no noteworthy multicollinearity (VIF

Table B1. Test of the Moderated Mediation Model

Path	Coefficient	SE	t-value	p-value	95% CI	Significance
FNS → MND_M	0.216	0.034	6.35	0.005	0.148, 0.284	Sig
MND_M → Y	0.293	0.041	7.15	0.003	0.213, 0.371	Sig
FNS → Y (direct)	0.128	0.029	4.41	0.006	0.070, 0.186	Sig
MND_M × Z → Y	0.094	0.022	4.27	0.001	0.051, 0.139	Sig
R^2 (Y)	0.438	–	–	–	–	–
Bootst indirect effect (Low Z)	0.089	0.022	–	–	0.045, 0.135	Sig
Bootst indirect effect (High Z)	0.045	0.016	–	–	0.018, 0.079	Sig

Appendix C. Robustness Test and Alternative Model Estimation

A robustness check was conducted to test the stability of our results based on an alternative estimation technique. In particular, we used Structural Equation Modeling (SEM) and Maximum Likelihood Estimation (MLE) in a compatible approach by AMOS 24.0, as an alternative to the regression-based method of the PROCESS macro. This confirmation ensures that the proposed links between the constructs (in particular, mediating and moderating effects) are not spuriously related by method bias or model misspecification.

The directional findings related to all the hypothesis paths were confirmed by the analysis conducted with the SEM. The overall indices of model fit came into acceptable range: CFI = 0.943, TLI = 0.937, RMSEA = 0.042, χ^2/df = 2.31, demonstrating good fit to the model. Not only that their all standardized path coefficients were significantly estimated and all were relatively the same with PROCESS. This implies that the moderated mediation formulation advanced in the paper applies across various estimation strategies, and lends support to the robustness and generalization of the findings.

Table C1. SEM Robustness Check for Moderated Mediation Model

Path Relationship	Std. Coefficient	CR	p-value	Result
FNS → MND_M	0.211	5.92	0.000	Support
MND_M → Realized Volatility (Y)	0.285	6.18	0.000	Support
FNS → Realized Volatility (direct)	0.122	4.17	0.000	Support
MND_M × Adaptiveness → Y	0.088	3.84	0.000	Support
Indirect effect via MND_M (Low Adaptiveness)	0.082	–	–	Sig
Indirect effect via MND_M (High Adaptiveness)	0.047	–	–	Sig

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