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Early Warning Systems for Financial Crisis Prediction: A Systematic Literature Review of Econometrics, Machine Learning and Uncertainty Indices

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Abstract

This study evaluates the integration of econometric methods, machine learning models, and uncertainty indices within the framework of Early Warning Systems (EWS) for financial crisis prediction in stock markets. A Systematic Literature Review (SLR) was conducted on studies published between 2008 and 2024, sourced from reputable databases such as Scopus, IEEE, and other international publishers. The review identifies three main objectives. First, the development of predictive models for market volatility and systemic risk using econometric and machine learning approaches. Second, the diagnosis of risk factors by incorporating macroeconomic indicators, commodity prices, geopolitical uncertainty, and sentiment data from big data sources. Third, the evaluation of policy implications and the role of composite indicators in maintaining financial stability. The dominant data categories include market data (prices, returns, volatility, sectoral indices), macroeconomic indicators (production, interest rates, leading indicators), commodities and energy (oil and gold), and measures of risk and uncertainty (GPR, GEPU, TPU, sentiment). Methodologically, studies employ time series econometrics (ARIMA, GARCH, VAR, spillover), machine learning, hybrid approaches, and indicator or policy-based frameworks. The findings reveal a growing trend toward multivariate and hybrid models, yet highlight limited integration across methods and data domains. This study emphasizes the need for integrative and operational EWS frameworks, tested across markets and crises, to ensure robustness, policy relevance, and practical utility.

Keyword: Crisis, Econometrics, EWS, Machine Learning, Uncertainty Sentiment.

1. INTRODUCTION

In recent years, Indonesia's investment landscape has undergone substantial transformation. Rising financial literacy, the proliferation of digital investment platforms, and increasing public interest in financial instruments have collectively fueled a sharp expansion in the investor base, particularly among retail participants. Data from the Financial Services Authority (*Otoritas Jasa Keuangan*/OJK) and the Indonesian Central Securities Depository (*Kustodian Sentral Efek Indonesia*/KSEI) indicate that the number of capital market investors has surpassed 15 million. In January 2025 alone, 289,527 new Single Investor Identification (SID) accounts were registered, almost double the growth recorded in January 2024, underscoring the growing inclusivity of public participation in the capital market. [1].

Amid this positive trend, assets such as equities and gold have emerged as the primary investment choices. Nevertheless, each asset exhibits varying degrees of sensitivity to macroeconomic dynamics. Furthermore, indicators such as the household purchasing power index reflect the consumption capacity of households, which plays a pivotal role in sustaining the performance of the domestic capital market. Accordingly, both macroeconomic and external factors constitute critical variables in shaping the trajectory of stock prices in Indonesia.

Despite these developments, a considerable gap remains between the analytical potential available and the actual behavior of most retail investors. Many retail participants tend to rely on instant information from social media or popular news sources that are often speculative and unverified. In contrast, effective investment decision-making should be grounded in systematic approaches such as fundamental and technical analysis, as well as the integration of macroeconomic and geopolitical variables through econometric models. Such comprehensive integration, however, remains relatively uncommon among individual investors in Indonesia.

Within the dynamics of financial markets, the interrelationship among interest rates, commodity prices particularly gold and household purchasing power forms a complex causal system. A reduction in policy interest rates, for instance, may stimulate capital flows into riskier instruments while simultaneously encouraging investors to seek safe haven assets such as gold. Fluctuations in gold and other commodity prices, in turn, influence inflation and production costs, ultimately affecting household purchasing power. A decline in purchasing power often serves as an early signal of economic slowdown, which may exert downward pressure on corporate performance and is reflected in the rising number of stocks reaching new lows in the market.

The international literature has underscored the importance of Early Warning Systems (EWS) in addressing stock market crises, particularly in emerging economies characterized by high volatility. Empirical studies in India, for example, have demonstrated the effectiveness of Hybrid Feature Selection (HFS) combined with Extreme Gradient Boosting (XGBoost) and Deep Neural Networks (DNN) in predicting crises with high accuracy [2]. Meanwhile, studies in China have integrated machine learning with the Non-dominated Sorting Genetic Algorithm II (NSGA-II) optimization algorithm and SHapley Additive exPlanations (SHAP) interpretability techniques, enabling the explanation of the relative contribution of financial indicators to crash risk [3]. Other studies have employed the Generalized Autoregressive Conditional Heteroskedasticity – Mixed Data Sampling (GARCH-MIDAS) approach to demonstrate that Geopolitical Risk (GPR) plays a significant role in shaping market volatility [4]. Indeed, classical models such as Autoregressive Integrated Moving Average (ARIMA) remain relevant for short-term forecasting [5].

Recent research trends indicate that crisis prediction can no longer rely on a single variable but instead requires a multivariate approach that integrates technical, fundamental, macroeconomic, and geopolitical indicators. However, in the Indonesian context, comprehensive studies that simultaneously incorporate variables such as GPR, Global Economic Policy Uncertainty (GEPU), Trade Policy Uncertainty (TPU), household consumption levels, policy rate adjustments, and gold prices remain scarce.

Accordingly, this study seeks to conduct a Systematic Literature Review (SLR) on EWS in capital markets, emphasizing the relevance of macroeconomic and geopolitical variables within Indonesia's context. The objective is twofold: first, to map the evolution of methods and variables employed in predicting stock market crises across different countries; and second, to identify gaps in the literature that could serve as a foundation for developing an early warning system tailored to the characteristics of the Indonesian capital market. Furthermore, this study endeavors to formulate a practical conceptual framework in which variables such as GPR, GEPU, TPU, household consumption levels, interest rates, and gold prices can be more effectively utilized to anticipate potential market turbulence. In doing so, the research not only enriches the academic literature but also provides practical insights for investors, regulators, and policymakers in mitigating risks and safeguarding the stability of the national capital market.

2. RELATED WORKS

The literature on EWS in stock markets demonstrates rapid methodological advancements, ranging from classical statistical models to more sophisticated machine learning approaches. Early studies predominantly employed traditional econometric methods such as ARIMA, which have proven effective in capturing linear patterns in time series data, particularly for short-term forecasting with relatively low prediction errors [5]. However, this method has been considered limited in capturing nonlinear patterns, thereby prompting the development of more adaptive hybrid models.

In the context of emerging markets, GPR has emerged as a key variable influencing stock market volatility. A study in China revealed that GPR significantly increases stock market volatility, with greater sensitivity to geopolitical threats than to geopolitical actions. Interestingly, the impact of GPR varies across countries: GPR originating from Brazil, China, and Venezuela was found to increase the volatility of the China Securities Index (CSI) 300 index, whereas GPR from Indonesia and Korea was associated with a reduction in volatility [4].

In addition to GPR, GEPU has also received considerable attention. Research examining Islamic stock markets found that GEPU exerts a negative impact on most Islamic stock returns, with the effect becoming more pronounced in the aftermath of the COVID-19 pandemic [6]. Similar findings have also been reported in emerging markets, where GEPU exerts a significant influence on stock market volatility, particularly in countries with weaker economic fundamentals [6] This reinforces the importance of integrating GEPU into the framework of EWS in emerging markets.

Another strand of research highlights the interaction between EPU, GPR, and the Volatility Index (VIX) in relation to sectoral stocks in the European Union. The findings reveal that European EPU exhibits stronger predictive power compared to GEPU or US-EPU. Moreover, the effects of EPU and GPR are asymmetric, exerting negative impacts during bearish conditions and positive impacts during bullish conditions [7]. The evidence points to the need for sectoral-level analysis as a fundamental component in constructing effective EWS.

The role of other external variables is equally critical. Research examining the interplay between the COVID-19 pandemic, oil prices, GPR, and EPU in the U.S. stock market found that the combination of these factors significantly increased volatility, particularly over the short-term horizon [8]. In line with this, studies in Europe confirm that crude oil prices exert a substantial influence on the energy sector, whereas the financial sector is more affected by macroeconomic and geopolitical uncertainties [9].

On the methodological front, recent developments have increasingly focused on the application of machine learning and deep learning. A study in India proposed a HFS approach combined with XGBoost and DNN. The findings indicate that the HFS-XGBoost model outperforms HFS-DNN in detecting stock market crises [2]. Meanwhile, research in China employed a combination of XGBoost, the Non-dominated Sorting Genetic Algorithm II (NSGA-II), and SHAP to generate more accurate and interpretable stock crash predictions. The classification accuracy reached 81% for small-cap stocks, while SHAP facilitated the explanation of the relative contribution of individual financial indicators to crash risk [3].

In addition to financial indicators, contemporary models increasingly incorporate multivariate information. For example, the Sentiment-Integrated Long Short-Term Memory (S_I_LSTM) framework integrates historical stock data, technical indicators, and sentiment analysis derived from Convolutional Neural Network (CNN), yielding notably higher accuracy than univariate models [10]. Another study compared various deep learning architectures (Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), CNN-LSTM, and Transformer) in stock price nowcasting and found that the standard LSTM remains the most reliable model, particularly under conditions of low price volatility [11].

urthermore, the dimension of cross-sectoral analysis has gained increasing attention. Sectoral dividend-yield-based models have been shown to outperform aggregate models in predicting real activity, particularly during crisis periods such as the Global Financial Crisis (GFC) and COVID-19. This superiority arises from the ability of sectoral models to filter out return components that merely reflect global sentiment [12].

Overall, the existing literature indicates that stock market crisis prediction has evolved from simple linear approaches toward nonlinear, machine learning based models that integrate multivariate variables. Nevertheless, a research gap persists in the Indonesian context, where key variables such as GPR, GEPU, TPU, household consumption levels, policy rate adjustments, and gold prices have yet to be systematically integrated into the framework of EWS.

3. METHOD

This study employs a SLR approach to identify, analyze, and synthesize prior research related to EWS in stock markets. The search strategy utilized keywords such as econometrics, crisis analysis, prediction, financial markets, and volatility, which are closely aligned with the research topic. The literature was collected from multiple databases, including Scopus, IEEE, and leading international journal publishers, covering the publication period 2008–2024. This timeframe was selected to capture the most recent developments over the past 16 years. The inclusion criteria were restricted to scholarly publications in indexed journals, international conference proceedings, and relevant working papers, while studies outside the scope or lacking a clear methodological framework were excluded from the analysis.

Following the identification stage, the selected literature was classified according to the journal quartile ranking (Q1–Q4) and its relevance to the research variables, including GPR, GEPU, TPU, household consumption levels, interest rates, and gold prices. This classification facilitated the assessment of both the quality and the contribution of the reviewed studies. Subsequently, a narrative synthesis approach was employed to summarize the methods, variables, and key findings of each study. The outcome of this stage enabled the authors to map methodological developments, thematic trends, and to identify research gaps that serve as the foundation for developing a conceptual framework of an early warning system tailored to the Indonesian capital market. An overview of the research methodological steps is illustrated in Figure 1.

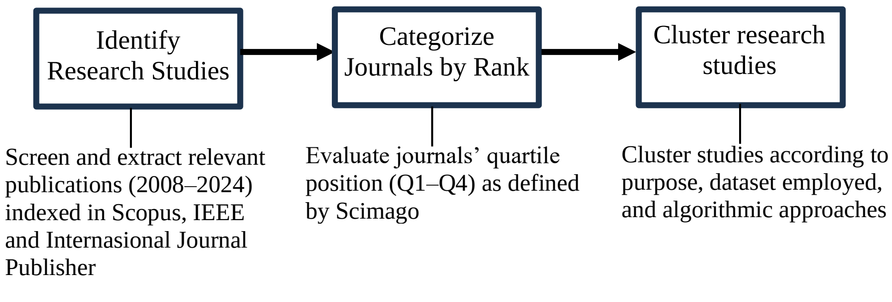

Figure 1. Research Methodology

4. RESULTS AND DISCUSSION

The literature survey covering the 2008–2024 period demonstrates that research on EWS in stock markets has advanced rapidly in terms of both methods and variables. In the early stage, classical econometric approaches such as ARIMA were widely employed for short-term forecasting; however, their limitations in capturing nonlinear patterns stimulated the development of hybrid models as well as machine learning and deep learning techniques (e.g., XGBoost, LSTM, and DNN), which have been shown to significantly enhance predictive accuracy.

In terms of variables, earlier research highlighted the significance of macroeconomic indicators, commodity prices, market volatility, and sector-specific information. More recent studies have extended this scope by incorporating GPR, GEPU, TPU, and household purchasing power, which have all been demonstrated to affect market volatility across various international contexts. These findings confirm that crisis prediction cannot rely on a single variable or model but instead requires multivariate integration. Nevertheless, comprehensive studies focusing on the Indonesian market remain scarce. Key variables such as GPR, GEPU, TPU, household consumption, interest rates, and gold prices have yet to be systematically examined in combination. To address this gap, the present study conducts a SLR. A summary of the prior research forming the basis of this analysis is presented in Table 1.

Table 1. Results from Journal Ranking

Title	Journal Ranking	Citation
Novel Stock Crisis Prediction Technique-A Study On Indian Stock Market	Q1	[2]
Stock Price Crash Warning In The Chinese Security Market Using A Machine Learning-Based Method And Financial Indicators	Q2	[3]
A Prediction Approach For Stock Market Volatility Based On Time Series Data	Q1	[5]
A Systematic Analysis And Review Of Stock Market Prediction Techniques Using Hybrid Approach	Q1	[13]
Capturing The Timing Of Crisis Evolution: A Machine Learning And Directional Wavelet Coherence Approach To Isolating Event-Specific Uncertainty Using Google Searches With An Application To COVID-19	Q1	[14]
Comparison Of The Performance Of Macroeconomic Finance Models For Financial Planning (Mfm-Fp) And Arima-Common Size In Forecasting Roe Of Real Estate Developers In The Stock Exchange Of Thailand	Q1	[15]
COVID-19 Pandemic, Oil Prices, Stock Market, Geopolitical Risk And Policy Uncertainty Nexus In The US Economy: Fresh Evidence From The Waveletbased Approach	Q1	[8]
Early Warning Signals For Stock Market Crashes: Empirical And Analytical Insights Utilizing Nonlinear Methods	Q1	[16]
Economic Policy Uncertainty, Geopolitical Risk, Market Sentiment, And Regional Stocks: Asymmetric Analyses Of The EU Sectors	Q1	[7]
EU Sectoral Stocks Amid Geopolitical Risk, Market Sentiment, And Crude Oil Implied Volatility: An Asymmetric Analysis Of The Russia-Ukraine Tensions	Q1	[9]
Evaluation Of Forecasting Methods From Selected Stock Market Returns	Q1	[17]
Financial Volatility Modeling With The GARCH-MIDAS-LSTM Approach: The Effects Of Economic Expectations, Geopolitical Risks And Industrial Production During COVID-19	Q2	[18]
Forecasting Real Activity Using Cross-Sectoral Stock Market Information	Q1	[12]
Geopolitical Risk And Tourism Stocks Of Emerging Economies	Q1	[19]
Impact Of Early COVID-19 Pandemic On The US And European Stock Markets And Volatility Forecasting	Q2	[20]
Incorporating Russo-Ukrainian War In Brent Crude Oil Price Forecasting: A Comparative Analysis Of ARIMA, TARMA And Ennreg Models	Q1	[21]
Macro-Financial Linkages In The High-Frequency Domain: Economic Fundamentals And The Covid-Induced Uncertainty Channel In US And UK Financial Markets	Q2	[22]
Manager Sentiment And Stock Returns	Q1	[23]
Novel Welfare State Responses In Times Of Crises: The COVID-19 Crisis Versus The Great Recession	Q1	[24]

Title	Journal Ranking	Citation
Nowcasting: The Real-Time Informational Content Of Macroeconomic Data	Q1	[25]
S_I_LSTM: Stock Price Prediction Based On Multiple Data Sources And Sentiment Analysis	Q2	[10]
Suttearima: Short-Term Forecasting Method, A Case: Covid-19 And Stock Market In Spain	Q1	[26]
Stock Price Nowcasting And Forecasting With Deep Learning	Q2	[11]
The Composite Leading Indicator For German Business Cycle	Q1	[27]
The Impact Of Oil And Gold Price Fluctuations On The South African Equity Market: Volatility Spillovers And Financial Policy Implications	Q1	[28]
The Effects of Economic Uncertainty and Trade Policy Uncertainty on Industry-Specific Stock Markets Equity	Q2	[29]
A global economic policy uncertainty index from principal component analysis	Q1	[30]
Geopolitical risk and volatility spillovers in oil and stock market	Q2	[31]

Based on Table 1, the selection of articles was conducted through a systematic process to ensure scientific rigor and relevance to the topic of EWS in stock market crises. To provide an objective benchmark of journal quality, the Scimago Journal Rank (SJR) quartile classification (Q1–Q4) was employed. The majority of the selected articles were published in Q1 and Q2 journals, underscoring that issues of economic uncertainty, GPR, financial volatility, and predictive approaches have received substantial recognition in high-impact academic forums. This composition not only highlights the methodological rigor of prior studies but also reflects the growing scholarly attention devoted to crisis prediction and financial market stability. The reviewed research encompasses a wide range of approaches, from conventional econometric models to computational techniques based on machine learning and deep learning. Following the validation of journal quality, the next step involved classifying the articles according to their methodological orientation and the variables examined, as summarized in Table 2.

Table 2. The Purpose of Big Data in Econometric

Aim/Purpose	Citation
Prediction – Build and test models for crisis/volatility forecasting	[2], [5], [10], [11], [13], [17], [26]
Diagnosis – Explain risk factors & channels (with macro, geopolitics, sentiment, big data)	[3], [7], [8], [9], [18], [19], [20], [21], [22], [23], [28], [29], [30], [31]
Policy/Evaluation – Evaluate indicators, frameworks, or policy implications for Early Warning System	[12], [14], [15], [24], [25], [27]

Research on EWS and financial crisis prediction generally converges on three main objectives. First, the development of predictive models using econometric methods, machine learning, and hybrid approaches to forecast market volatility, crisis timing, and systemic risk. Second, the diagnosis of risk factors through fundamental analysis of macroeconomic conditions, commodities, geopolitical uncertainty, and the integration of big data sources such as social media and news sentiment, which illustrate the complexity of crisis transmission channels. Third, the evaluation of policy implications, namely the assessment of the effectiveness of composite indicators, leading indices, and cross-sectoral information to support decision making, risk management, and macroprudential policy. This classification helps to identify patterns and priorities in financial crisis early warning research and serves as the foundation for further synthesis in the data grouping presented in Table 3.

Table 3. Data Categories

Data Category	Variable	Citation
Market Data	Stock Price, Return, Volatility, Sektoral Index.	[2], [3], [5], [11], [12], [13], [16], [17], [25], [26]
Macroeconomic Indicator	Economic Fundamentals, Leading Indicators, Production, Interest Rates	[14], [15], [18], [22], [24], [27]
Commodities & Energi	Oil, Gold, Global Energy Market	[8], [9], [21], [28], [31]
Risk, Uncertainty, and Big Data Sentiment	Event Based Data	[7], [9], [10], [18], [19], [20], [23], [29], [30]

According to Table 3, financial market data comprising stock prices, returns, sectoral indices, and multiple measures of volatility represents the most frequently utilized category. Many studies rely on this type of data to construct econometric or machine learning models for forecasting crises and generating early warning signals. The second most frequently employed category consists of macroeconomic indicators, such as Gross Domestic Product (GDP), industrial production, interest rates, and composite leading indicators, which are essential for linking financial dynamics with real economic activity. Commodity and energy data particularly oil and gold prices serve as another source of shocks that influence volatility spillovers and contagion effects across markets. Finally, data on risk, uncertainty, and sentiment, including GPR indices, economic policy uncertainty measures, and big data sentiment from investment managers or social media, provide valuable insights into how expectations and perceptions trigger financial instability. This classification highlights the dominant forms of information employed in early warning system (EWS) and crisis prediction research and forms the basis for the subsequent stage of analysis focusing on the models and algorithms applied, as presented in Table 4.

Table 4. Algorithm / Model / Technique Used

Algorithm / Model / Technique	Citation
Time Series Econometrics	[5], [17], [18], [22], [25], [27], [28], [29], [31]
Machine Learning and Deep Learning	[2], [3], [10], [11]
Hybrid/Mixed Approaches (Econometric and Multi Source)	[12], [13], [15], [16]
Indicator Based & Policy Evaluation Approaches	[7], [8], [9], [14], [19], [20], [21], [23], [24], [30]

Table 4 illustrates that studies on financial crisis EWS have adopted a broad range of methods, encompassing time-series econometric modeling, machine learning, hybrid techniques, and indicator/policy-based evaluations. Traditional econometric tools (e.g., ARIMA, GARCH, Vector Autoregression (VAR), spillover models) have been instrumental in analyzing volatility and systemic risk. Meanwhile, machine learning and deep learning algorithms (including LSTM, classifiers, and graph-based methods) have been employed to anticipate crashes and rebounds. Hybrid approaches leverage the strengths of both paradigms, whereas indicator-based analyses highlight composite measures and policy frameworks aimed at ensuring macro-financial stability.

Nevertheless, several limitations remain evident. These include the frequent separation of econometric models, uncertainty indices, and sentiment measures; the reliance of machine learning models on limited datasets; and indicator-based approaches that are often descriptive and lack operational applicability. Consequently, future research directions call for an integrative framework that consolidates econometric data, the predictive power of machine learning, and uncertainty indices within a single EWS model. Such a framework should also be tested across markets and crisis periods to ensure robustness, practical utility, and policy relevance.

5. CONCLUSION

This study conducts a SLR on EWS for financial crisis prediction in stock markets, covering literature published between 2008 and 2024. The review identifies three primary research objectives: (1) the development of predictive models employing econometric approaches, machine learning, and hybrid frameworks to forecast market volatility, crisis timing, and systemic risk; (2) the diagnosis and explanation of risk factors, including macroeconomic fundamentals, commodity prices, geopolitical uncertainty, and big data sentiment that reflect the complexity of financial instability transmission channels; and (3) policy evaluation and the use of indicator frameworks, particularly composite indices and cross-sectoral information, to support decision making and macroprudential policy.

From a data perspective, most studies rely on financial market variables (prices, returns, volatility, and sectoral indices), followed by macroeconomic indicators (GDP, industrial production, interest rates, and leading indicators), commodities and energy (oil and gold prices), as well as risk and uncertainty indices (GPR, GEPU, TPU, and sentiment measures). From a methodological standpoint, four dominant approaches are identified: time-series econometrics (ARIMA, GARCH, VAR, and spillover models); machine learning and deep learning techniques (LSTM, classifiers, and graph-based models); hybrid frameworks that integrate econometrics with multi source data; and indicator and policy-based evaluations.

Although research on EWS has demonstrated rapid methodological progress, several limitations can still be identified. Most studies continue to treat econometric models, uncertainty indices, and sentiment variables as separate instruments, resulting in the absence of an integrated EWS framework. While machine learning offers promising prospects, its application is often constrained by limited data coverage and insufficient technical detail in validation, which in turn restricts the generalizability of findings. On the other hand, indicator and policy-based approaches tend to remain descriptive and have yet to be fully developed into operational and applicable warning signals.

Bridging these methodological divides offers a particularly compelling direction for future research. The intersection of econometrics, machine learning, and risk/uncertainty modeling provides a multidimensional lens through which financial crises can be better understood, predicted, and mitigated. Econometrics ensures statistical rigor and causal interpretation; machine learning enhances predictive accuracy and adaptability; and uncertainty indices capture the behavioral, policy, and geopolitical dimensions of risk. Together, they form the foundation for a next generation EWS that is both theoretically grounded and empirically responsive to dynamic market conditions.

Importantly, this integrative framework holds significant relevance for emerging markets such as Indonesia, where financial volatility often stems from the interplay between interest rate adjustments, commodity price fluctuations (particularly gold and energy), and shifts in consumer purchasing power. For instance, the 2020 COVID-19 shock demonstrated how declining interest rates, rising gold prices, and weakening consumption simultaneously pressured the Indonesian Stock Exchange (IDX), leading to a surge in stocks hitting new lows. Embedding these interdependent factors within an EWS framework would not only enhance predictive reliability but also strengthen the capacity of policymakers, regulators, and investors to respond proactively to systemic risks.

Accordingly, future research should focus on developing an integrated and operational early warning system that combines the rigor of econometrics, the predictive power of machine learning, and the explanatory capacity of uncertainty indices. Such frameworks should be empirically tested across markets, crises, and sectors to ensure robustness, interpretability, and policy relevance. For Indonesia, this direction is particularly valuable as it offers a data driven pathway to anticipate financial stress, safeguard investor confidence, and reinforce national economic resilience.

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