Louvain School of Management

# Analyzing the impact of news on stock price predictions using high and low frequency signals

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# Abstract

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# 1 Introduction

In a rapidly evolving financial landscape, the role of information in shaping market behavior has become increasingly significant. One of the most intriguing and complex challenges is understanding the relationship between prediction markets and their influence on stock price movements. This thesis addresses the problem of quantifying how predictive signals derived from prediction markets impact stock prices.

## 1.1 The Current World of Prediction Markets and Stock Prices

In today's financial world, markets are flooded with a wide range of information that can impact investor behavior (Li et al., 2014). Prediction markets, also known as event futures or information markets, aggregate individual opinions and probabilities about future events, offering valuable signals about the direction of various economic, political or social factors (Waitz and Mild, 2013; Wolfers and Zitzewitz, 2004). These markets provide a unique opportunity for investors to gauge future expectations and anticipate market movements.

## 1.2 Research Question

This thesis focuses on the research question: *How do prediction markets signals affect stock prices?* To answer this, we explore the potential mechanisms through which these signals influence investor behavior and, by extension, the market valuation of assets. By investigating prediction markets signals, this research aims to build a comprehensive model for stock price prediction that accounts for the full spectrum of information available to investors.

To address this question, we adopt a comparative modeling strategy. Specifically, we assess the relevance and performance of a global modeling approach — a single regression model applied across all stocks, incorporating both returns and exogenous variables common to all assets — versus a stock-specific model, where a distinct model is trained for each individual stock. This methodology enables to determine whether a shared structure, enriched by exogenous information from prediction markets, can generalize across different stocks, or whether asset-specific nuances require tailored models.

## 1.3 Managerial Relevance

This research holds substantial managerial relevance for Delphia, a Canadian fintech specializing in data-driven investment strategies. The implications are outlined below :

**1. Enhanced data-driven investment strategies:** By analyzing how predictive signals from prediction markets influence stock prices, Delphia can refine its investment models. Integrating these signals into algorithms could enhance decision-making processes and potentially improve portfolio performance (Waitz and Mild, 2013).

**2. Improved forecasting accuracy:** Prediction markets aggregate public sentiment and probabilities about future events, offering valuable insights to anticipate market trends. By combining these signals with Delphia's existing data models, the accuracy of stock price predictions could be significantly improved, leading to more informed investment decisions and better risk management.

**3. Detection of market inefficiencies and early trends:** This research can aid Delphia in identifying market inefficiencies and emerging trends by leveraging prediction market data. This proactive approach could allow the company to capitalize on shifts in market dynamics before competitors.

**4. Risk management optimization:** Incorporating prediction market signals would bolster Delphia's ability to detect potential risks during periods of volatility or uncertainty. This enhanced risk management capability could help protect the company's portfolios from significant losses and reduce exposure to high-risk investments.

**5. Innovation in investment products:** The findings could inspire the development of new financial products that utilize prediction market signals. For instance, funds tailored to exploit trends from these markets could offer clients innovative, high-return investment options.

**6. Competitive advantage through strategic information use:** Expanding Delphia's data integration to include prediction markets could provide a distinct competitive edge. By harnessing diverse information sources, the company can position itself as a leader in identifying and acting on emerging trends, attracting clients and increasing its market presence.

Overall, this research aligns closely with Delphia's mission of leveraging data to inform investment decisions. The insights gained can optimize strategies, improve predictive accuracy and strengthen the company's position in the fintech sector.

## 1.4 Thesis Structure

This thesis is organized into chapters. The second chapter, Literature Review, examines the existing literature on prediction markets, stock price dynamics and recent advancements in global modeling applied to finance. This sets a comprehensive foundation for the research. In the third chapter, Methodology, the focus is on data collection methods, the techniques employed to implement global modeling and the integration of prediction markets to enhance the understanding of stock market movements. This chapter provides a detailed explanation of the methodological framework, including the implementation of prediction market data and global modeling. Chapter four, Analysis of the results, presents the findings of the empirical analysis, showcasing how prediction markets influence stock prices and evaluating the effectiveness of global modeling techniques in interpreting these dynamics. The fifth chapter, Discussion, interprets the results, compares them with existing literature and discusses their implications for both theory and practice. Finally, the Conclusion summarizes the research, highlights its implications for investors and regulators and suggests areas for future research.

# 2 Literature Review

This section examines previous theories and research on the valuation of information and its influence on financial markets. It reviews key studies, theoretical frameworks and findings relevant to understanding the connection between prediction markets and stock market responses.

## 2.1 Prediction Markets

Prediction markets are platforms where participants trade contracts that pay out based on the outcome of future events (Wolfers and Zitzewitz, 2004). These markets aggregate the individual predictions of participants, turning them into a collective forecast of the likelihood that an event will occur. The concept of prediction markets is rooted in the idea that the collective wisdom of a diverse group of individuals, each with access to different information and insights, can generate more accurate forecasts than any individual expert (Bossaerts et al., 2022). These markets function similarly to financial markets (Wolfers and Zitzewitz, 2004), where participants buy and sell contracts based on their predictions of future outcomes. For instance, participants might buy a contract that pays out if a specific political event occurs, such as the election of Trump against Kamala Harris during the 2024 presidential race (Mongrain and Stegmaier, 2024), or if a company meets a certain financial target.

One of the key features of prediction markets is their ability to aggregate information. As discussed by Bossaerts et al., 2022, these markets incorporate diverse viewpoints, enabling them to reflect the collective intelligence of participants. This phenomenon is often referred to as the ”wisdom of crowds”. Berg et al., 2008, have shown that prediction markets can outperform individual experts in terms of forecasting accuracy, as they incorporate a wide range of opinions.

These markets are typically structured as winner-take-all markets or vote-share markets. In winner-take-all markets (Dai et al., 2021), participants predict a single outcome and those who predict the correct event share the prize. This market model offers a fixed payout for the correct prediction, which is typically the same for all winners. Vote-share markets involve trading based on the estimated proportion of votes or shares in a specific outcome, often used for more detailed or continuous predictions, such as estimating the exact vote share in an election or market share in a competition (Dai et al., 2021).

Research has shown that prediction markets can effectively predict not only political events but also economic trends, such as the likelihood of a recession or the movement of stock prices (Wolfers and Zitzewitz, 2004). These markets function as a tool to forecast economic indicators, company performance, or even geopolitical events. By integrating real-time information and the collective insights of a diverse set of participants, prediction markets offer a unique and valuable source of predictive signals that can inform decision-making in various domains, including finance. For example, Google estimates its market capitalization using prediction markets to forecast its value prior to an initial public offering (Berg et al., 2009).

## 2.2 Conceptual and theoretical framework

### 2.2.1 Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH), developed by Eugene Fama, posits that asset prices fully and instantaneously reflect all available information (Naseer, 2016). This theory assumes that markets are highly efficient in processing and integrating information into prices, leaving no opportunity for consistent outperformance based on publicly available data.

In this context, prediction markets can be viewed as a mechanism to enhance market efficiency by aggregating dispersed and heterogeneous information from a diverse set of participants (Downey, 2024). These markets function by incentivizing participants to trade based on their knowledge, insights, or expectations of future outcomes, effectively pooling collective intelligence.

Unlike traditional financial markets, which rely on a combination of fundamental and technical analysis, prediction markets are explicitly designed to reflect probabilities of future events (Nti et al., 2020; Naseer, 2016). By doing so, they may uncover ”hidden” information that would otherwise remain unintegrated into asset prices. This ability to aggregate a wide array of viewpoints and data sources positions prediction markets as a complementary tool for improving the informational efficiency of financial markets.

### 2.2.2 Investor behavior

**Herding :** Herding behavior is a significant phenomenon in financial markets, where investors mimic the actions of others rather than relying on their own private information. This tendency often arises during periods of market stress, leading to deviations of asset prices from their intrinsic values. Research highlights that herding is particularly pronounced in emerging markets, where information asymmetry and market inefficiencies are more prevalent (Ah Mand et al., 2023). For example, in the Malaysian stock market, evidence suggests that herding behavior exhibits non-linear characteristics, with variations between up and down market conditions. Shariah-compliant stocks tend to demonstrate herding more significantly during upward market movements, while conventional stocks show limited evidence of herding. This behavior has critical implications for market stability, as it may amplify volatility and hinder market efficiency.

**Financial influencers :** Financial influencers on social media platforms, particularly those categorized as ”mega influencers” with over one million followers, have a unique ability to shape investor behavior and market dynamics. Studies demonstrate that posts from these influencers can significantly affect investor attention, trading volume and stock price volatility (Keasey et al., 2024). However, their influence on stock returns is limited, requiring posts with extreme sentiment from top influencers to elicit short-lived impacts on returns. This aligns with the ”noise trader” hypothesis, which posits that uninformed trading triggered by such influencers introduces temporary mispricing that reverses over time. By analyzing over 16 million Instagram posts, researchers have highlighted the importance of sentiment and engagement metrics, such as comment volume, in amplifying the visibility and potential market impact of influencer content. These findings underscore the dual-edged role of influencers in promoting market participation while potentially fostering instability through noise trading.

## 2.3 Forecasting Methods:

Forecasting time-series data, especially in a panel setting involving multiple stocks and exogenous signals, such as prediction market data, requires a thoughtful selection of modeling strategies. In this research, we compare two paradigms commonly discussed in the forecasting literature: local modeling and global modeling.

### 2.3.1 Panel data

Panel data refer to a dataset in which multiple time series are stacked row-wise, each representing a different entity (for example, stock or asset) observed over time (Baltagi, 2007). This structure allows for modeling both the temporal dynamics and the cross-sectional differences between entities. By pooling information between entities, panel data techniques can improve forecast accuracy, especially when entities are influenced by common factors or share similar patterns. Panel data methods, such as fixed- or random- effects models, enable more robust predictions by accounting for both shared and entity-specific effects.

### 2.3.2 Local Modeling Approach

Local modeling, also referred to as the univariate approach, involves training a separate model for each stock in the dataset. This approach treats each time series as an independent regression problem, fitting a distinct function to predict future values based on the historical data of that specific series alone. Traditional time series approaches such as ARIMA (Box, 1970) or exponential smoothing are typically applied in this context.

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t$$

where $Y_t$ is the value of the time series at time $t$, $\phi_1, \ldots, \phi_p$ are autoregressive parameters, $\theta_1, \ldots, \theta_q$ are the moving average parameters and $\epsilon_t$ is the error term.

According to Montero-Manso and Hyndman, 2021, local models offer several advantages. They provide flexibility to model series-specific behavior, enabling the capture of unique patterns in individual stocks. This approach also ensures high interpretability for each asset, making it easier to identify the specific factors influencing the performance of a stock. Moreover, local models do not rely on any assumptions of similarity between different time series, which allows each stock to be modeled independently.

However, Montero-Manso and Hyndman, 2021 underline that these models also have important limitations. One major drawback is the high risk of overfitting, especially when the historical data available for each series is limited. Additionally, local models do not scale well as the number of time series increases, since each stock requires its own model to be trained and maintained. They also struggle to capture common trends or shared external influences, such as signals from prediction markets that can impact several stocks simultaneously. Finally, local modeling often requires manual feature engineering and domain expertise to effectively integrate relevant external variables.

### 2.3.3 Global Modeling Approach

Global modeling involves training a single model across all time series, learning from shared patterns while still accounting for entity-specific characteristics through identifiers and feature engineering. As demonstrated by Montero-Manso and Hyndman, 2021 , this approach leverages the cross-sectional structure of panel data and often leads to better performance, particularly when series are related in behavior or influenced by common external signals such as prediction market data.

In a global model, all stocks are pooled together into a single regression problem, with the model learning to forecast based on the combined dataset. This approach can be represented as:

$$\hat{y}_{i,t} = f(X_{i,t}, \theta)$$

where $\hat{y}_{i,t}$ is the predicted value for the stock $i$ at time $t$. $X_{i,t}$ represents the characteristics (including stock identifiers, temporal features and exogenous variables) and $\theta$ is the set of parameters shared across all stocks.

For tree-based models such as XGBoost (Chen and Guestrin, 2016), which are particularly effective for global modeling, this can be expressed as:

$$\hat{y}_{i,t} = \sum_{k=1}^{K} \alpha_k f_k(X_{i,t})$$

where $\hat{y}_{i,t}$ is the predicted value for the stock $i$ at time $t$. $f_k(X_{i,t})$ is the output of the $k$-th decision tree, $\alpha_k$ is the weight of the tree and $K$ is the total number of trees.

The global approach offers several key benefits. By enabling shared learning across multiple stocks, it improves generalization and helps reduce the risk of overfitting. The combination of data from different series increases the effective sample size, which in turn reduces variance and enhances statistical efficiency. This broader data context allows the model to detect long-memory patterns and complex nonlinear relationships that local models may fail to capture due to limited data. Furthermore, the global approach can automatically learn dependencies across series and identify common external influences without the need for manual specification. It also allows for a more efficient integration of exogenous variables, such as prediction market signals, which often affect multiple stocks in similar ways.

From a theoretical perspective, Montero-Manso and Hyndman, 2021 demonstrated that global models can approximate the forecasts of any local models under mild conditions, provided that they use sufficient memory. More formally, for a set of time series $\{X_1, X_2, ..., X_K\}$, each of length $T$, the global forecasting function $g$ learns a mapping:

$$g : R^M \to R^H, \quad \text{where } M \ll T \text{ is the memory (lag) and } H \text{ is the forecast horizon}$$

Importantly, to match the flexibility of local models, global models may require a longer memory $G$, such that:

$$\sum_{i=1}^{K} L_i = G$$

where $L_i$ is the memory length used in the local model for series $i$. This insight motivates the design of global models with extended lag windows or deeper architectures to capture richer temporal dynamics.

Recent empirical evidence shows surprisingly good performance of global methods even on heterogeneous groups of time series that cannot be considered intuitively similar. This challenges the conventional wisdom that global models are only beneficial when time series are related or generated by similar processes. As Montero-Manso and Hyndman, 2021 demonstrate, purposefully naive algorithms derived from global modeling principles, such as global linear models adapted to least squares, deep networks, or high-order polynomials, can achieve superior accuracy compared to traditional local approaches, often with far fewer parameters.

### 2.3.4 Why Global Modeling Supports This Research

This thesis investigates the impact of prediction markets on stock prices. Prediction market signals are typically exogenous, global in nature and not specific to a single asset. A global forecasting model is well suited to capture such influences, as it can learn shared patterns across all stocks while integrating prediction market features as common.

The global modeling approach is particularly relevant for this research for several reasons. Prediction markets often generate signals that impact multiple stocks at once, especially those within related sectors or subject to similar macroeconomic forces. By pooling information across different stocks, global models are better equipped to detect correlations between prediction market signals and stock price movements even when the effects are subtle at the level of individual stocks. In addition, global models can automatically learn complex interactions between these signals and stock-specific characteristics without the need for manual specification. This approach also offers increased statistical efficiency, which is especially valuable when dealing with financial time series known for their high noise-to-signal ratio.

Moreover, global models are particularly relevant in the presence of sparse or short time series, as is often the case in financial forecasting. By pooling information, these models achieve higher statistical efficiency and robustness, making them well suited for analyzing the relationship between prediction markets and stock prices, where the available history of prediction market data may be limited.

# 3 Methodology

This section outlines the methodological framework used to investigate the influence of predictive signals from prediction markets (Polymarket) on stock market data (Delphia).

## 3.1 Data Sources and Structure :

### 3.1.1 Stock Market Data (Delphia)

The Delphia dataset provides the following key attributes: *the trading date*, acting as the temporal reference for all stock-related activities; *the ticker*, serving as the unique identifier of a stock; and the daily percentage change in the stock price, defined as *returns*, which is used as the target variable for predicting future movements. This dataset is essential for representing the financial market environment and is preprocessed to ensure consistency in time series, including filling missing dates and normalizing features.

### 3.1.2 Prediction Market Data (Klashi)

The Klashi dataset contains information about prediction market signals, capturing a variety of economic and sector-specific events. The dataset includes attributes such as the market's probability estimate for a given event, represented as value and the time at which the prediction market value was recorded, indicated as timestamp.

## 3.2 Data Preprocessing

The data preprocessing phase is crucial for preparing both stock market and prediction market data for analysis (Daniel, 2019). This section details the steps taken to clean, transform and integrate these datasets to enable effective modeling.

### 3.2.1 Prediction Market Data Processing

The prediction market data from Kalshi required a series of preprocessing steps to make it suitable for time series analysis. First, quarterly datasets were collected for Tesla (production forecasts), Netflix (subscriber growth) and Meta (daily active user predictions), covering different quarters of 2024. These datasets, which contained probabilistic estimates for company-specific events, were integrated using the `bind_rows()` function to obtain one prediction dataset per company.

To ensure temporal consistency, timestamps were converted to a standardized date format, enabling proper alignment with stock market data. Given that prediction values could change multiple times within a single day, the data was aggregated at the daily level using the mean prediction value per day.

A complete daily sequence was then created for each company and missing values were handled using a dual approach: linear interpolation (`na.approx()`) for short gaps and last observation carried forward (`na.locf()`) for remaining missing values (Moritz and Bartz-Beielstein, 2017, Bokde et al., 2018). This ensured both temporal continuity and the preservation of recent market sentiment when no updates were available.

Finally, each company's cleaned dataset was labeled with a company identifier and all were merged into a single panel dataset, forming a structured and coherent input for subsequent analysis.

### 3.2.2 Stock Market Data Integration

The stock market data provided by Delphia was filtered to retain only the companies relevant to the analysis—Tesla, Netflix and Meta. After selection, this data was processed to align precisely with the cleaned prediction market datasets, using date and ticker as keys for the join. This integration resulted in a unified dataset containing both daily stock returns and associated prediction market signals.

To address gaps caused by non-trading days such as weekends and holidays, missing stock return values were replaced with zeros, ensuring temporal continuity across the series (Subha, 2024). The time frame was restricted to start from March 22, 2024, to focus the analysis on the most recent and relevant period.

Finally, the dataset was refined by selecting only the necessary variables for modeling and the column names were adjusted to improve readability and consistency in the merged data structure.

### 3.2.3 Train-Test Split Strategy

To ensure a realistic evaluation of model performance, a time-based train-test split was applied, preserving the chronological order of observations. This approach reflects real-world forecasting conditions, where models are trained on historical data and used to predict future unseen values. The splitting process was conducted individually for each company's dataset, allowing custom training and testing sets that respect the specific temporal structure of each time series. By maintaining this temporal integrity, the strategy avoids data leakage and provides a more reliable assessment of the predictive capabilities of the model. (Tashman, 2000)

### 3.2.4 Modeling Approach Implementation

To assess the predictive power of prediction market signals on stock returns, two complementary modeling strategies were implemented: a local time series approach and a global machine learning approach. This dual setup enables a comparison between models that focus on individual stock behavior and those that exploit patterns across all stocks jointly.

The local modeling approach involved fitting separate ARIMA models for each stock, Tesla, Netflix and Meta. These models were designed to capture stock-specific temporal dynamics without using information from other stocks. The forecasts generated by these independent models were later compared to those from the global approach to evaluate relative performance.

In contrast, the global modeling approach used a single XGBoost model trained on the entire panel dataset. This model was constructed to learn simultaneously from all stocks by incorporating both cross-sectional and temporal patterns. Several key features were engineered to enhance model performance:

- Stock identifiers were transformed into dummy variables to capture stock-specific effects (Baltagi, 2007).
- Temporal features (e.g., day of the week, month, quarter) were extracted from date information to model time-based seasonality (Dancho, n.d.).
- Prediction market signals were included as exogenous predictors, enabling the model to capture their influence on stock returns (Dancho, n.d.).

- All numeric variables were normalized to ensure balanced influence during training (Dancho, n.d.).

This setup allows the global model not only to learn idiosyncratic behavior for each stock but also to uncover potential interactions and shared structures between them, especially regarding how prediction market signals can differentially affect stock performance.

### 3.2.5 Performance Evaluation Framework

To ensure an objective comparison between the local and global modeling approaches, a robust evaluation framework was implemented. This framework leverages a variety of performance metrics to assess model accuracy from multiple perspectives (Hyndman and Koehler, 2006). The chosen evaluation metrics are:

- MAE (Mean Absolute Error): Measures the average magnitude of errors in the predictions, giving insight into overall model accuracy.
- RMSE (Root Mean Square Error): Focuses on larger errors, highlighting models that perform well in avoiding large discrepancies.
- R-squared: Quantifies the proportion of variance in the stock returns explained by the model, indicating its explanatory power.

This comprehensive set of metrics ensures a multifaceted evaluation, allowing for a detailed comparison of the models' strengths and weaknesses. The inclusion of the Diebold-Mariano, (Diebold and Mariano, 2002), test further enhances the robustness of the evaluation by providing statistical evidence on whether one model consistently outperforms the other. The framework facilitates a thorough assessment of how well the local and global models capture the impact of prediction market signals on stock returns, directly addressing the research question of how these signals influence stock prices.

# 4 Analysis of Results

This section presents the empirical findings from our comparative analysis of local and global modeling approaches for forecasting stock returns with prediction market signals. We evaluate model performance, analyze the relationship between prediction markets and stock prices and examine how different modeling approaches capture this relationship.

## 4.1 Model Performance Comparison

### 4.1.1 Accuracy Metrics

The performance of both modeling approaches, local ARIMA models and the global XGBoost model, was evaluated using multiple accuracy metrics on the test dataset. The Table 1 summarizes these results.

Table 1: Performance Comparison of Local and Global Models

| **Model** | **MAE** | **RMSE** | **$R^2$** |
|---|---|---|---|
| ARIMA (TSLA) | 0.0135 | 0.0226 | 0.0507 |
| ARIMA (NFLX) | 0.0081 | 0.0124 | 0.0081 |
| ARIMA (META) | 0.0075 | 0.0107 | 0.0309 |
| XGBoost (Global) | **0.01** | **0.02** | **0.0** |

### 4.1.2 Statistical Comparison of Models with the Diebold-Mariano Test

To rigorously evaluate the performance difference between our individual ARIMA models and the global XGBoost model, we applied the Diebold-Mariano test. This statistical test, developed by Diebold and Mariano, 2002, determines whether the difference in predictive performance between two competing models is statistically significant.

**Test Methodology :** The Diebold-Mariano test compares the forecast errors of two models and evaluates whether their difference is statistically significant. In our case, we compared the Root Mean Square Errors (RMSE) of the individual ARIMA models for each company (Tesla, Netflix and Meta) with the global XGBoost model.

For each company, we generated simulated error series based on the observed RMSE values, then applied the Diebold-Mariano test with a forecast horizon $h = 1$ and a quadratic loss function (power=2). This approach allowed us to assess the statistical significance of performance differences between the two modeling approaches.

**Test Results :** The Diebold-Mariano test results reveal interesting differences in model performance across companies:

- **Tesla (TSLA)**: The test indicates no significant difference between the two models (p-value = 0.4505, DM statistic = -0.7579). This suggests that for Tesla, both modeling approaches offer comparable performance.
- **Netflix (NFLX)**: The test indicates that the ARIMA model is significantly better than the global model (p-value = 0.0002, DM statistic = -3.9153). The strongly negative DM statistic and very low p-value confirm the superiority of the ARIMA model for predicting Netflix returns.
- **Meta (META)**: Similar to Netflix, the test indicates that the ARIMA model is significantly better than the global model (p-value ¡ 0.0001, DM statistic = -4.363). The strongly negative DM statistic and extremely low p-value demonstrate a clear superiority of the ARIMA model for Meta.
- **Average across companies**: When considering the average performance across all companies, the test confirms that ARIMA models are generally more performant than the XGBoost model (p-value = 0.0448, DM statistic = -2.0346).

The Diebold-Mariano test allows to conclude that individual ARIMA models are generally more performant than the global XGBoost model for stock return prediction in our context. This conclusion is particularly robust for Netflix and Meta, while for Tesla, both approaches offer statistically equivalent performance.

This rigorous statistical analysis confirms the importance of considering company-specific characteristics in stock return modeling and suggests that the ”one-size-fits-all” approach of the global model presents significant limitations despite its theoretical advantages. These findings challenge our initial hypothesis that a global model would better leverage prediction market signals across multiple stocks, indicating that the idiosyncratic nature of each stock’s relationship with its corresponding prediction market may be more important than the shared structure we attempted to capture.

# 5 Discussion

This section compares the results obtained with those of previous studies and outlines the practical and theoretical implications of the study. It also explores potential limitations and alternative interpretations of the findings.

# 6 Conclusion

This final section summarizes the main findings of the study, discusses its limitations and suggests avenues for future research.

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# Appendix

Abstract :

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