**Abstract (250-300 words)**:

* This is a concise summary of the entire thesis, including the research question, methods, results, and conclusion.83232222222222322222222222222w3wwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwewwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwwww

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### **1. Introduction**

**Background and Context:**

This paper focuses on the relationship between **sentiment**, particularly music-based sentiment and **financial market behavior**, specifically the UK stock market. Understanding this connection is crucial, as investor sentiment is a well-documented driver of short-term market movements. Music sentiment, derived from platforms like Spotify, offers a unique and real-time proxy for mood, allowing researchers to explore sentiment beyond traditional measures like news headlines or social media. By examining the **effects of music sentiment on different indices**, such as FTSE100, FTSE 250, and FTSE Small Cap, this paper adds to the growing body of behavioral finance literature that links external sentiment factors to market outcomes, especially in the context of **seasonality**, **market capitalization**, and **liquidity constraints**.

**Research Question**

How does music-based sentiment (SWAV) affect stock returns in the UK market across different indices (FTSE100, FTSE 250, and FTSE Small Cap)?

How do liquidity constraints and external controls like the TED spread or COVID-19 stringency index influence the sentiment-return relationship?

**Objectives**

Quantifying the impact of music sentiment (SWAV) on UK stock market returns.

Analyzing how the impact of sentiment varies across market indices, particularly between small-cap, mid-cap, and large-cap stocks.

Examining the role of seasonality and holiday effects, such as the Christmas period, in amplifying or reducing sentiment-driven market movements.

Investigating the moderating effects of liquidity constraints and macroeconomic conditions (e.g., TED spread, COVID-19 stringency index) on the sentiment-return relationship.

Evaluating the consistency of sentiment-driven effects over different time horizons, from short-term (1 day) to medium-term (10 days).

**Contribution:**

**Innovative Sentiment Measure**: By using SWAV, a real-time music-based sentiment measure, your study introduces a novel proxy for mood and explores its influence on market behavior, expanding beyond traditional sentiment indicators like news or social media.

**Focus on Market Capitalization**: By analyzing the relationship between sentiment and stock returns across different indices, you provide insights into how smaller, less liquid stocks may be more sentiment-sensitive, contributing to the literature on **market segmentation** and **investor behavior**.

**Liquidity and Macroeconomic Controls**: Your study enriches the understanding of how liquidity constraints and broader economic conditions moderate the effects of sentiment, particularly in periods of heightened uncertainty like the **COVID-19 pandemic**.

**Seasonality Insights**: By exploring the interaction between sentiment and market behavior during specific seasonal periods (e.g., Christmas), your research sheds light on how temporary mood shifts affect financial markets.

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### **Literature Review (1,600-2,000 words)**

### 1. Efficient Market Hypothesis (EMH) and Its Challenges

The **Efficient Market Hypothesis (EMH)**, introduced by **Fama (1970)**, posits that financial markets are informationally efficient, meaning that stock prices reflect all available information at any given time. This idea makes it difficult for investors to consistently achieve returns that exceed the market average without taking on more risk. **Fama (1965)** earlier demonstrated that stock prices follow a random walk, supporting the weak form of EMH, which asserts that historical prices cannot predict future movements. **Fama (1991)** expanded on the semi-strong form of EMH, stating that prices adjust quickly to new public information, though he acknowledged anomalies such as the size and value effects, which challenge market efficiency.

**Samuelson (1965)** provided mathematical justification for EMH, showing that prices would follow a random walk if markets are efficient. **Jensen (1978)** affirmed EMH's robustness, stating it had more empirical support than most other financial theories, though he conceded the existence of some anomalies. However, critics such as **Jegadeesh and Titman (1993)** identified momentum effects, where past winners continue to perform well, challenging the notion of market efficiency. **Shiller (2000)** and **Thaler (1985)** documented how behavioral biases can lead to market inefficiencies, such as overreactions to news. **Grossman and Stiglitz (1980)** argued that perfectly efficient markets are unattainable because there would be no incentive to gather information. **Lo (2004)** introduced the **Adaptive Markets Hypothesis**, proposing that market efficiency evolves over time as investors adapt to changing conditions. These critiques suggest that external sentiment measures, like music sentiment, might expose temporary inefficiencies in markets.

### 2. Sentiment and Stock Market Behavior

The influence of sentiment on stock market behavior has been extensively studied, with evidence showing that both internal and external sentiment drive market movements. **Bollen et al. (2011)** introduced Twitter sentiment as a predictor of stock market trends, demonstrating how social media sentiment influences short-term market fluctuations. Similarly, **Sprenger et al. (2014)** explored the role of Twitter sentiment in financial markets, further validating the power of external sentiment to predict stock returns. **Edmans, Garcia, and Norli (2007)** examined how national mood, influenced by international soccer match outcomes, significantly affected stock returns, revealing that negative outcomes led to market declines in the losing country.

**Tetlock (2007)** provided compelling evidence that media sentiment, particularly pessimistic news, can predict declines in stock prices, while optimistic news correlates with rising prices. **Da et al. (2015)** took a different approach by using Google search volume data to measure fear-related sentiment, finding that increased fear correlates with lower stock prices. These studies underscore the significant role that various forms of sentiment play in shaping short-term market movements.

Additionally, **Hirshleifer and Shumway (2003)** examined how external factors, such as weather, affect sentiment and stock returns. They found that sunny days, associated with improved mood, lead to positive stock returns. **Baker and Wurgler (2006)** and **Schmeling (2009)** highlighted that sentiment-driven mispricing is more prevalent in small-cap and volatile stocks. Collectively, these studies lay a foundation for investigating how music sentiment, as an external sentiment indicator, can influence stock market behavior.

### 3. Music and Mood

Research on the connection between music and mood reveals that music is a powerful tool for influencing and reflecting emotions. **North and Hargreaves (1996)** found that background music in public spaces affects collective moods, demonstrating its potential to shape social behavior and public sentiment. **DeNora (2000)** emphasized that music serves as an emotional regulator in daily life, helping individuals manage their emotional states and, in turn, reflecting broader societal moods. **Juslin and Västfjäll (2008)** explored the mechanisms behind music-induced emotions, identifying emotional contagion, episodic memory, and musical expectancy as key processes through which music evokes emotional responses.

**Koelsch (2010)** linked music-induced emotions to neurological activity, showing that music activates brain regions associated with emotional processing, thereby highlighting the biological basis for music’s influence on mood. **Rentfrow and Gosling (2003)** found that music preferences are linked to personality traits and emotional states, suggesting that societal emotional climates can be mirrored in musical trends. Recent research by **Spotify (2018)** demonstrated that shifts in music consumption patterns during significant societal events, such as economic crises, reflect collective emotions and moods, making music a useful proxy for gauging public sentiment.

These findings indicate that music not only affects individual emotions but also serves as a reflection of broader public sentiment, making it a valuable tool for analyzing how mood influences societal trends, including financial markets.

### 4. Music Sentiment and Market Behavior

Recent studies have investigated the link between music sentiment and stock market behavior, proposing that music-based sentiment provides a novel proxy for investor mood. **Edmans et al. (2021)** introduced a real-time music-based sentiment measure using Spotify data, demonstrating that positive music sentiment correlates with higher same-week stock returns but leads to declines in the following week, likely due to sentiment-driven mispricing. This study highlights the value of music sentiment as an alternative sentiment indicator that captures public mood in real time, going beyond traditional measures like news or social media sentiment.

Building on this, **Nguyen et al. (2022)** analyzed the impact of music sentiment on the Vietnamese stock market, revealing that music sentiment affects both stock returns and volatility. Notably, foreign music sentiment, such as that from the U.S. and Hong Kong, also had a measurable impact on Vietnam's stock market performance, demonstrating the global reach of music sentiment’s influence on market behavior. These studies suggest that music sentiment offers a unique lens for understanding investor mood and its effect on financial markets, particularly during periods of heightened uncertainty or volatility.

### 5. Seasonality and Stock Market Behavior

Seasonality in stock market behavior has been documented extensively, with a focus on anomalies like the **holiday effect** and the **January effect**. **Ariel (1990)** found that stock returns are significantly higher before holidays, while **Kim and Park (1994)** confirmed the holiday effect, showing stock return anomalies around public holidays. **Keim (1983)** explored the **January effect**, where small-cap stocks outperform larger ones, revealing a key seasonal pattern. **French (1980)** demonstrated the **weekend effect**, where stock returns are typically lower on Mondays. **Haugen and Jorion (1996)** showed the persistence of these effects over time, reinforcing the idea that seasonality plays a critical role in market behavior. **Meneu and Pardo (2004)** added that small investors' optimism drives the pre-holiday effect. The **Santa Claus Rally**, studied by **Washer et al. (2016)**, shows a notable increase in stock prices during the last week of December and early January, predominantly in small-cap stocks. These studies provide a backdrop for examining how music sentiment might interact with seasonality in stock markets.

### 6. Market Capitalization, Index Type, and Returns

The relationship between market capitalization and returns has been a focus in sentiment studies, with small-cap stocks often exhibiting stronger sentiment-driven movements. **Fama and French (1992)** introduced the three-factor model, which links small-cap stocks to higher returns due to their size-related risk premium. **Brown and Cliff (2004)** and **Kumar and Lee (2006)** found that sentiment has a more significant effect on small-cap stocks, as these stocks are more speculative and volatile. **Baker and Wurgler (2006)** showed that small-cap stocks are more prone to mispricing due to their higher idiosyncratic risk and lower liquidity. **Schmeling (2009)** confirmed that investor sentiment has a stronger predictive power in small-cap stocks internationally. **Dash and Maitra (2018)** added that small- and mid-cap stocks, with higher returns, are more sentiment-sensitive. Finally, **Gromb and Vayanos (2010)** highlighted how limits to arbitrage exacerbate the impact of sentiment on smaller, less liquid stocks, which is particularly relevant when analyzing how music sentiment influences the UK market across different indices.

### 7. Liquidity Constraints and Limits to Arbitrage

Liquidity plays a crucial role in determining stock returns, especially for less liquid stocks. **Amihud and Mendelson (1986)** demonstrated that stocks with lower liquidity require higher returns to compensate for higher trading costs. **Datar (1998)** and **Amihud (2002)** extended this by examining how illiquidity affects stock returns in both cross-sectional and time-series contexts, showing that liquidity is a key determinant of the liquidity premium. **Pastor and Stambaugh (2001)** introduced liquidity risk into asset pricing models, finding that stocks with higher liquidity risk have higher expected returns. **Brunnermeier and Pedersen (2009)** and **Gromb and Vayanos (2010)** explained how liquidity constraints and limits to arbitrage lead to more pronounced mispricing, particularly in small-cap stocks. **Shleifer and Vishny (1997)** emphasized the importance of liquidity in maintaining market efficiency, showing how illiquidity leads to persistent market inefficiencies. These findings are crucial for understanding how liquidity constraints might amplify the impact of music sentiment on UK stock returns.

### 8. COVID-19 Stringency Index

The COVID-19 pandemic introduced unprecedented volatility in financial markets, influenced by global lockdowns and restrictions. The **COVID-19 stringency index** captures the severity of these restrictions and their impact on market behavior. **Al-Awadhi et al. (2020)** found that rising COVID-19 cases and stringent lockdowns led to significant negative stock returns, driven by uncertainty. **Baker et al. (2020)** documented the unprecedented volatility in global stock markets, showing that sentiment and fear of the pandemic significantly impacted market behavior. **Zhang, Hu, and Ji (2020)** highlighted the role of investor sentiment in driving market volatility during the pandemic, showing that markets responded strongly to pandemic-related news. **Cevik (2022)** found that sentiment-driven market fluctuations were more pronounced in the early stages of the pandemic, with negative news having a greater impact than positive news. The inclusion of the stringency index helps to isolate the effects of music sentiment from broader economic disruptions caused by the pandemic, providing clearer insights into how sentiment impacts stock returns in periods of extreme uncertainty.

### 9. Applicability to the UK Market

While global studies provide valuable insights, testing music sentiment in the UK context is essential to understand its impact on local market dynamics. **Antoniou et al. (2013)** found that investor sentiment influences stock returns in the UK, particularly during high-sentiment periods when high-beta stocks outperform, suggesting potential mispricing. **Garcia (2013)** demonstrated that sentiment-driven market inefficiencies are more pronounced during recessions, with the UK experiencing sharper declines in negative sentiment phases. **Kumar and Lee (2006)** showed that retail investor sentiment drives volatility, particularly in small-cap stocks, a key sector in the UK market. **Barberis et al. (1998)** emphasized that waves of optimism or pessimism among investors lead to mispricing, particularly in smaller, less liquid stocks. These findings suggest that sentiment, including music sentiment, could influence UK market behavior, creating potential arbitrage opportunities in small-cap stocks or during economic stress, making the UK an ideal setting for testing music-based sentiment as a market indicator.

### **Data and Methodology 1,200-1,600 words**

### Data Sources

This study relies on a combination of sentiment data, stock market performance data, and control variables to analyze the relationship between music sentiment and stock market returns.

Music sentiment is derived from Spotify’s API, which provides access to song metadata, the specific variables is valence—a measure of a song's emotional positivity. The Spotify Web API allows for the retrieval of content metadata and popularity rankings. For this study, music sentiment is aggregated using data from the Spotify Charts for the top 200 streamed songs in the UK, collected daily. This real-time sentiment measure serves as a unique indicator of collective mood, with valence scores from the top songs aggregated into a sentiment index reflective of the emotional tone in the UK.

Stock market data is sourced from various indices representing different segments of the UK market, reflecting the performance of large-cap, mid-cap, and small-cap stocks. The **FTSE 100** index, tracking the largest 100 companies listed on the London Stock Exchange, is sourced from **Investing.com**. The **FTSE 250** index, which captures the next 250 largest companies, and the **FTSE Small Cap** index, representing smaller, more volatile companies, are also sourced from **Investing.com**. Additionally, the **MSCI World Stock Market Indices**, used for comparative purposes, are sourced from the same platform.

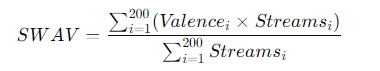
To control for external factors that may influence stock market returns, several variables are incorporated. **Weather data**, particularly cloud cover, is sourced from the **Open-Meteo weather forecast API**, helping to account for mood changes linked to weather variations. The **Economic Policy Uncertainty (EPU)** index, sourced from **policyuncertainty.com**, captures weekly news-based uncertainty in economic policy. The **Aruoba-Diebold-Scotti Business Conditions Index (ADS)**, from the **Federal Reserve Bank of Philadelphia**, provides macroeconomic activity data, while the **VIX** index, sourced from the **Chicago Board Options Exchange (CBOE)**, tracks volatility expectations, offering insights into global market risk sentiment. The **TED Spread**, sourced from **FRED** (<https://fred.stlouisfed.org/series/TEDRATE>), measures the difference between interbank loan rates and U.S. Treasury bills, indicating liquidity risk. Finally, the **COVID-19 Stringency Index**, from the **University of Oxford’s COVID-19 Government Response Tracker**, captures the severity of government-imposed pandemic restrictions, controlling for the effects of the pandemic on market behavior.

### Variables

This study investigates the relationship between music sentiment and stock market performance in the UK from **January 1, 2017, to December 31, 2023**, with some models covering **January 1, 2017, to December 31, 2022**, due to data limitations on the TED Spread. The key variables include the dependent variable, the independent variable, and several control variables to account for external factors influencing stock returns.

The **dependent variable** is the **change in FTSE Price** across three indices: **FTSE 100**, **FTSE 250**, and **FTSE Small Cap**. The change in price is measured over four different time horizons: **1-day, 3-day, 5-day, and 10-day periods**. This allows the study to capture both short- and medium-term impacts of sentiment on stock returns, offering insights into immediate and prolonged market reactions to shifts in music sentiment.

The **independent variable** is the **Change in SWAV (Stream-Weighted Average Valence)**, which is a measure of national music sentiment. SWAV aggregates the emotional positivity (valence) of the top 200 songs streamed in the UK, weighted by the number of streams for each song. Higher SWAV values indicate a more positive overall emotional tone, reflecting the collective mood of the population. This measure is crucial as it serves as a proxy for national sentiment. SWAV is calculated as follows:



Where **Valence** represents the emotional positivity of a song, and **Streams** represent the number of times the song was played. Changes in SWAV are observed over the same time periods as the changes in FTSE prices, aligning the independent and dependent variables for direct comparison.

Several **control variables** are included to ensure that other factors are not confounding the relationship between music sentiment and stock returns. The **Change in Economic Policy Uncertainty (EPU)** captures variations in economic policy uncertainty as reflected in news coverage, providing insight into political and economic instability that could influence market behavior. The **Change in Aruoba-Diebold-Scotti Business Conditions Index (ADS)** is included as a weekly measure of macroeconomic activity, accounting for broader economic trends that might impact stock prices. Additionally, the **VIX (Implied Volatility Index)**, commonly referred to as the "fear gauge," is used to measure market volatility expectations, serving as a proxy for global investor risk aversion.

The study also includes **Rolling Average Change in Deseasonalised Cloud Cover (DCC)**. DCC controls for the effect of weather on investor mood and behavior by adjusting for the typical seasonality of cloud cover and capturing any deviation from normal patterns. This allows the model to account for how weather conditions, particularly cloud cover, influence sentiment and stock returns. Furthermore, the **Previous Period FTSE Performance** is included to control for momentum and autoregressive effects, ensuring that the influence of past stock performance is properly captured. The **MSCI World Index**, representing global stock market trends, is also used as a control, providing a broader international context for understanding the UK market's movements.

In addition to these basic controls, several **extra control variables** are included to capture specific market conditions and seasonal effects. A **Festivity Dummy** is used to account for the potential sentiment shifts that occur during the holiday period from **December 24 to January 8**, commonly associated with the "Santa Claus Rally." This variable is set to **1** during this period and **0** otherwise. The **TED Spread Dummy** captures periods of heightened liquidity risk, with a value of **1** if the TED Spread (the difference between the interest rates on interbank loans and U.S. Treasury bills) is in the top 10th percentile and **0** otherwise. An interaction term between SWAV and the TED Spread dummy is also included to explore how music sentiment interacts with market stress.

Lastly, the **COVID-19 Stringency Index** is incorporated as a continuous variable, not as a dummy. This index measures the severity of government-imposed restrictions during the pandemic, with higher values indicating more stringent lockdown measures. The inclusion of the COVID-19 Stringency Index helps control for the impact of pandemic-related restrictions on stock market behavior, ensuring that the effects of music sentiment are isolated from broader economic disruptions caused by the pandemic.

### Methodology

The first step in this study is to assess the **direct relationship** between **SWAV (Stream-Weighted Average Valence)** and **FTSE stock returns** without incorporating any control variables. This initial analysis provides a baseline understanding of whether there is an unadjusted, direct correlation between music sentiment and stock market performance. By examining the raw relationship between SWAV and the changes in the FTSE indices (FTSE 100, FTSE 250, and FTSE Small Cap), we aim to capture the immediate influence of sentiment on stock returns. This baseline model allows us to explore whether sentiment, as captured by music preferences, has a standalone effect on stock market behavior, which will later serve as a comparison point for more complex models.

Following this initial step, we proceed to estimate a **basic regression model** that includes core variables to examine the relationship between music sentiment and stock market returns in greater detail. The dependent variable in this model remains the **change in FTSE price** for the FTSE 100, FTSE 250, and FTSE Small Cap indices. The independent variable is the **Change in SWAV**, which captures national music sentiment based on the valence and streaming volume of the top 200 songs in the UK. To account for other factors that might influence stock returns, several control variables are introduced. These controls include the **Change in the Aruoba-Diebold-Scotti Business Conditions Index (ADS)**, reflecting overall economic activity, and the **Change in Economic Policy Uncertainty (EPU)**, which captures uncertainty related to economic policy. The model also controls for **previous FTSE performance**, which accounts for momentum effects, the **MSCI World Index** to adjust for global market trends, **Deseasonalised Cloud Cover (DCC)** to control for weather effects on investor behavior, and the **VIX (Implied Volatility Index)**, a proxy for global risk sentiment. This model provides a more refined understanding of how music sentiment impacts stock market performance while accounting for key economic, global, and environmental factors.

In the next stage, we introduce additional controls to further refine the model and account for specific market conditions that may influence sentiment and stock returns. **Model 2** incorporates the **Festivity Dummy** to control for the period between **December 24 and January 8**, which is often associated with the "Santa Claus Rally." This period typically exhibits deviations in both SWAV and stock market behavior, with stock returns generally increasing due to year-end portfolio adjustments and holiday-related optimism. Adding the Festivity Dummy ensures that any observed relationship between SWAV and FTSE changes during this period is not confounded by seasonal effects.

In **Model 3**, the **COVID-19 Stringency Index** is introduced as a control to account for the significant disruptions caused by the pandemic. The COVID-19 pandemic led to changes in both sentiment and stock market behavior due to strict lockdown measures and government-imposed restrictions. By adding the COVID-19 Stringency Index, the model controls for these pandemic-related disruptions, ensuring that the impact of music sentiment on stock returns is captured accurately. An **interaction term between SWAV and the COVID-19 Stringency Index** is also included to explore whether the relationship between music sentiment and stock performance was stronger during periods of stricter lockdown measures, when music consumption patterns and investor mood were more closely linked.

Finally, in **Model 4**, the **TED Spread Dummy** is introduced to account for periods of heightened liquidity risk and market stress. The TED Spread, which measures the difference between interbank lending rates and U.S. Treasury rates, saw significant increases during times of financial uncertainty, particularly in 2020. The TED Spread Dummy takes the value of **1** during periods when the spread is in the top 10th percentile, indicating high market stress, and **0** otherwise. An **interaction term between SWAV and the TED Spread** is included to investigate whether music sentiment has a stronger influence on stock returns during periods of high market stress, when external sentiment factors like music may play a larger role in market behavior. This final model allows the study to explore how the relationship between sentiment and stock returns changes during periods of heightened financial instability.

The study also conducts a **window period analysis**, testing the model across different time frames: **1-day, 3-day, 5-day, and 10-day periods**. This approach allows for the examination of both immediate and lagged effects of sentiment on stock market returns. The **1-day window** captures the immediate reaction of the stock market to changes in music sentiment, which is useful for understanding short-term volatility. The **3-day and 5-day windows** allow the study to explore medium-term effects, where sentiment may have a more sustained impact on investor behavior and stock performance. Finally, the **10-day window** captures the longer-term impact of music sentiment on stock returns, providing insights into how mood-driven behaviors accumulate over a longer period. This multi-window approach ensures that the temporal dynamics of the sentiment-stock return relationship are thoroughly examined, allowing the study to identify whether the effects of music sentiment on stock market returns are short-lived or persist over time.

### **4. Empirical Results 1,200-1,600 words**

* Direct relationship results:
* **Basic Regression Results:** Present and interpret the results of your initial regression model without any controls.
* **Festivity Dummy Analysis:** Show the results after adding the Festive Dummy and discuss any changes in the significance and coefficients of the variables.
* **COVID Stringency Controls:** Analyze how adding the COVID Stringency and interaction terms impacts the model.
* **TED Spread Controls:** Discuss the results with the TED Spread included, focusing on the interaction effects and their significance.
* **Window Period Analysis:** Compare the results across different time windows, highlighting any patterns or differences observed in the impact of sentiment and other controls.

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### **5. Discussion 1,200-1,600 words**

* **Comparison of Models:** Summarize and compare the findings from each model. Discuss how the addition of controls influenced the relationships between sentiment and market returns.
* **Interpretation of Results:** Provide a deeper interpretation of why certain variables (e.g., TED spread) have stronger effects in certain models or for specific indices (e.g., FTSE 100 vs. FTSE Small Cap).
* **Implications for Theory and Practice:** Discuss the broader implications of your findings for understanding market behavior, especially in times of financial stress or during festive periods.

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### **6. Conclusion**

* **Summary of Key Findings:** Recap the main findings from your analysis, focusing on the impact of sentiment and the role of different controls.
* **Research Contributions:** Highlight the unique contributions your research makes to the literature.
* **Limitations and Future Research:** Acknowledge any limitations in your study (e.g., data constraints, model assumptions) and suggest areas for future research.

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### **8. Appendices**

* **Supplementary Material:** Include any additional tables, figures, or technical details that support your analysis but are not central to the main text.

This structure will help you present your research in a coherent and logical manner, ensuring that each stage of your analysis builds on the previous one and contributes to answering your research question.