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Tracking and Predicting Health Trends: A Google Trends-Based Time-Series Analysis

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Abstract

Purpose: This study analyzes global health-related search trends using Google Trends data from January 2021 to the present. It focuses on elderly health, odor management, beauty products, deodorization, and industry-related health topics to uncover long-term trends, seasonal variations, and forecast patterns. These insights reflect public interest and market behavior in health-related areas. **Research Design & Data, Methodology**: Time-Series Analysis, Correlation Analysis, and ARIMA forecasting were applied to analyze to Google Trends data. Time-Series Analysis identified patterns and seasonality; Correlation Analysis explored relationships among search terms; and ARIMA predicted search trends for the next 12 weeks. **Research Results**: Elderly health searches steadily increased, indicating rising awareness. Odor and deodorization showed strong seasonality, peaking in warmer months. Beauty product searches remained relatively stable, with spikes during promotional periods. Industry-related health concerns varied, reflecting workplace policies and regulations. Correlation results revealed strong links between odor and deodorization, and moderate connections between elderly health and beauty products. **Conclusion**: Google Trends effectively captures public interest in health topics. The study provides valuable insights for public health professionals, businesses, and policymakers. Future research should integrate external variables and machine learning methods to enhance prediction accuracy and monitor emerging health concerns.

Keywords : Health, Google Trends, Time-Series Analysis, Consumer Behavior, Predictive Modeling

JEL Classification Code : I12, C53, D83, M31, J81

1. Introduction

In today's digital era, online search behavior has become a key indicator of public interest and awareness across various domains, particularly in the field of health (Eysenbach, 2009). Google Trends serves as a valuable tool for analyzing global search patterns, offering insights into how people's health concerns and priorities shift over time (Nuti et al., 2014).

Since early 2021, major global events—including the ongoing effects of the COVID-19 pandemic, advancements

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in healthcare, and an increased focus on personal well-being—have significantly influenced health-related search trends (Mavragani, 2020). Understanding these trends provides critical insights into societal health concerns and the underlying factors driving public interest in different health-related topics.

This study examines Google Trends data from January 2021 to the present, focusing on search interest in elderly health, odor management, beauty products, deodorization, and industry-related health concerns. By tracking fluctuations in search interest over time, this research aims to identify key patterns, detect seasonal variations, and analyze correlations between different topics (Husnayain et al, 2019). The study contributes to the growing body of knowledge on digital health trends and their implications for both individuals and industries (Dugas et al., 2012).

The primary objective of this research is to analyze global health-related search trends and uncover significant patterns, relationships, and external influences on public health concerns. Specifically, the study aims to:

• Identify overall trends in health-related searches and assess their long-term changes (Ayers et al., 2014).
• Examine correlations between different search topics, such as the relationship between aging populations and the increasing interest in beauty products (Mavragani & Ochoa, 2019).
• Investigate seasonal variations to determine whether certain topics, such as odor management and deodorization, exhibit periodic fluctuations throughout the year (Huang et al., 2009).
• Analyze the impact of external factors, including global events, pandemics, and policy changes, on search trends (Effenberger et al., 2020).
• Utilize machine learning models to predict future health-related search trends based on historical data (Carneiro & Mylonakis, 2009).

By achieving these objectives, this research will provide valuable insights into public health awareness and behavioral shifts in response to societal and environmental changes.

Studying health-related search trends is crucial for multiple reasons. First, it enhances public health awareness by enabling health organizations and policy makers to identify emerging health concerns and implement timely interventions. For instance, a surge in searches related to elderly health may indicate an increasing need for elderly care resources (Mavragani, 2021). Additionally, this research provides important market and industry insights, as companies in healthcare, personal care, and the pharmaceutical industry can utilize search trend data to better understand consumer behavior, optimize product development, and refine marketing strategies (Choi & Varian, 2012). For example, a rise in searches for deodorization may indicate a growing demand for hygiene-related products (Ayyoubzadeh et al., 2020).

Moreover, monitoring search trends serves as an early detection system for potential health crises by identifying sudden spikes in searches related to symptoms or disease outbreaks (Eysenbach, 2020). This proactive approach allows healthcare professionals to respond more effectively to emerging public health concerns (Carneiro & Mylonakis, 2009). Additionally, this study contributes to behavioral and social research, offering a deeper understanding of how global populations seek health-related information and how social, economic, and environmental factors influence these behaviors (Mavragani, 2019). The findings can help shape public health campaigns, educational initiatives, and future health policies (Hu et al., 2020).

Another key aspect of this research is its predictive potential for decision-making. By leveraging machine learning techniques, this study can forecast upcoming trends in health-related searches, enabling businesses, healthcare providers, and governments to anticipate shifts in public interest and demand (Lazer et al., 2014). Predictive analysis allows organizations to proactively address health-related behaviors and implement strategic planning in response to expected trends (Tado, 2021).

In conclusion, analyzing health-related search trends provides valuable insights into public health awareness, consumer behavior, and societal changes. By examining the relationship between digital health data and real-world applications, this study seeks to bridge the gap between online search behavior and practical decision-making (Nuti et al., 2014). The insights derived from this research can be applied to academic studies, public health initiatives, market strategies, and policy development, ultimately contributing to a deeper understanding of how people engage with health information in the digital age (Eysenbach, 2020).

2. Literature Review

The increasing reliance on online search engines as a source of health-related information has led to growing interest in using search data for public health research (Eysenbach, 2009). Google Trends, a widely recognized tool for analyzing search behavior, provides real-time insights into how people engage with health-related topics across different regions and time periods (Nuti et al., 2014). Researchers have utilized Google Trends data to examine various aspects of public health, including disease surveillance, mental health trends, seasonal variations in health concerns, and shifts in health awareness due to external factors such as pandemics or economic conditions (Effenberger et al., 2020; Mavragani, 2020).

Several studies have demonstrated the effectiveness of Google Trends data in identifying health trends and predicting outbreaks of diseases. For example, Ginsberg et al. (2009) conducted one of the earliest studies on Google search data, showing that influenza-related search terms could predict flu outbreaks in real time. This approach, known as "infodemiology," has since been expanded to analyze search trends for various health conditions, such as respiratory illnesses, mental health disorders, and lifestyle-related diseases (Tado, 2021). Similarly, Mavaragani (2020) illustrated how Google search trends can serve as an early warning system for pandemics by tracking changes in symptom-related searches before official health reports confirm an outbreak.

Beyond disease surveillance, search trend analysis has also been used to study behavioral changes in response to health-related events. For instance, Ayers et al. (2014) explored how public interest in e-cigarettes fluctuated over time by analyzing Google search trends, concluding that online search behavior reflects societal attitudes toward emerging health topics. Similarly, research on elderly health and aging-related concerns has shown that search interest in elderly care and age-related health issues has increased in response to demographic shifts and policy changes (Jaidka et al., 2021).

Another area of interest in Google Trends research is the analysis of seasonal patterns in health-related searches. Studies have found that search interest in certain topics, such as allergies, respiratory illnesses, and deodorization, follows predictable seasonal cycles (Huang et al., 2009). For example, Yang et al. (2017) found that searches for "flu symptoms" peak during colder months, while searches for "deodorant" and "body odor" increase in the summer. These seasonal patterns suggest that search behavior is influenced not only by personal health concerns but also by environmental factors.

Additionally, correlations between different health-related search terms can provide valuable insights into public perception and health behaviors. For example, research has explored the relationship between mental health and beauty trends, finding that increased interest in self-care and cosmetic products often coincides with periods of higher anxiety and stress (Brewster & Cox, 2018). Similarly, studies have examined how industrial and environmental concerns influence health-related searches, with findings indicating that pollution levels and urbanization trends impact search behavior for respiratory and odor-related topics (Choi & Varian, 2012).

Despite the growing body of research using Google Trends data, challenges remain in interpreting search behavior accurately. One limitation is the potential for external events, media coverage, and misinformation to artificially inflate search interest in specific topics. For example, major news events or celebrity endorsements can cause temporary spikes in search trends that do not necessarily reflect long-term changes in public interest (Lazer et al., 2014). Additionally, differences in search behavior across cultures and languages pose challenges in comparing trends on a global scale (Mavragani & Ochoa, 2019).

Given these considerations, this study aims to build on existing research by analyzing global search trends related to health topics from 2021 to the present. By incorporating time-series analysis, correlation studies, and predictive modeling, this research seeks to provide a comprehensive understanding of how public interest in health-related issues evolves over time. The findings will contribute to the broader field of digital health research, offering insights that can inform public health initiatives, business strategies, and future research in online health behavior analysis.

3. Research Methods

3.1. Data Collection

This study utilizes Google Trends data to analyze global search trends related to health from January 2021 to the present. Google Trends has been widely used in public health research for tracking and analyzing health-related information-seeking behavior (Eysenbach, 2009; Mavragani & Ochoa, 2019).

The dataset includes search interest in five key health-related topics:

• Elderly health (concerns related to aging and elderly care)
• Odor management (interest in body odor, deodorization, and related concerns)
• Beauty products (search behavior related to cosmetic and self-care products)
• Deodorization (interest in air purification and hygiene-related odor management)
• Industry-related health topics (occupational health concerns and environmental health trends)

The data was extracted from Google Trends using relative search interest scores, which range from 0 to 100, where 100 represents the peak search volume for a given keyword within the specified period and region (Choi & Varian, 2012). The dataset is structured on a weekly basis, enabling detailed time-series analysis to track long-term patterns and fluctuations (Lazer et al., 2014).

3.2. Data Processing and Preprocessing

Before conducting the analysis, the dataset underwent several preprocessing steps to ensure accuracy and reliability.

First, date formatting was applied to convert the period column into datetime format, enabling effective time-series analysis and visualization (Ginsberg et al., 2009). This transformation ensured that the dataset could be accurately plotted and analyzed based on chronological trends.

To maintain data consistency, any missing values were identified and addressed using linear interpolation, a widely used method for estimating missing values based on surrounding data points (Tado, 2021). This approach preserved the natural flow of the dataset without introducing artificial distortions.

Since Google Trends data is normalized—meaning that values are scaled relative to the highest point of search interest within a given time frame—it was essential to approach standardization with caution (Mavragani, 2020). Instead of directly comparing absolute values across different categories, the analysis focused on identifying trends and variations within each category. This ensured that differences in search volume across topics did not lead to misleading conclusions.

An outlier detection process was conducted to identify sudden spikes or drops in search interest. These anomalies were examined to determine whether they were caused by significant external events such as major news coverage, policy changes, or seasonal influences (Carneiro & Mylonakis, 2009). Detecting these outliers allowed for a more accurate interpretation of the data by distinguishing between organic search trends and external factors that may have temporarily influenced search behavior. By implementing these preprocessing techniques, the dataset was refined to provide a solid foundation for further analysis, ensuring that the findings would be both meaningful and reliable.

3.3. Analytical Methods

To gain meaningful insights from the data, the study employs multiple analytical approaches, including Time-Series Analysis, Correlation Analysis, and Predictive Modeling.

3.3.1. Time-Series Analysis

To examine long-term patterns and fluctuations in search interest, trend analysis is conducted by visualizing search trends over time (Choi & Varian, 2012). This approach helps identify consistent growth, decline, or shifts in public interest across different health-related topics. By analyzing search behavior over an extended period, the study can determine whether certain topics have gained or lost relevance over time (Dugas et al., 2012).

Additionally, seasonality detection is performed to identify cyclical trends in search interest. Some health-related topics exhibit seasonal patterns, such as an increase in searches related to deodorization during summer months, when concerns about body odor are more pronounced (Yang et al., 2017). By recognizing such seasonal variations, the study can assess whether fluctuations in search interest are recurring trends rather than random variations.

To improve data clarity, moving average and smoothing techniques are applied. Statistical methods, such as the 7-day moving average, help reduce short-term fluctuations and highlight overall trends (Tado, 2021). These smoothing techniques filter out noise from the dataset, allowing for a clearer visualization of long-term patterns in public interest.

3.3.2. Correlation and Relationship Analysis

To explore potential relationships between different health-related search topics, Pearson and Spearman correlation analyses are conducted (Effenberger et al., 2020). These methods assess the strength and direction of associations between variables. For example, the study examines whether search interest in elderly health and beauty products is correlated, as aging populations may show increased interest in self-care and cosmetic solutions (Mavragani, 2021). Identifying such relationships can provide insights into shifting health priorities and consumer behavior.

In addition to direct correlation analysis, a cross-correlation analysis is performed to detect possible time-lag effects between different search topics (Lazer et al., 2014). This approach determines whether changes in search interest for one topic lead to delayed changes in another. For instance, the study investigates whether an increase in public awareness of elderly health is followed by a delayed rise in searches for beauty and self-care products, suggesting a growing interest in aging-related beauty solutions.

3.3.3. Predictive Modeling for Future Research

If applicable, this study explores the potential for predicting future search trends using machine learning techniques. Models such as ARIMA (Auto Regressive Integrated Moving Average) and Facebook Prophet are considered to forecast upcoming shifts in search behavior based on historical data (Carneiro & Mylonakis, 2009). These models allow for the estimation of future interest in health-related topics, providing valuable insights for businesses, policy makers, and public health organizations.

To improve prediction accuracy, feature engineering is employed, incorporating factors such as seasonality patterns, trend decomposition, and external event markers (Ginsberg et al., 2009). By integrating these elements, the study aims to create a more robust predictive framework, capable of identifying future trends and informing proactive decision-making in health-related industries.

Through these analytical approaches, the research seeks to provide a comprehensive understanding of how public interest in health-related topics evolves over time, responds to external events, and can be projected into the future.

4. Research Results and Discussion

4.1. 4-week moving average trends

The graph in Figure 1 presents the 4-week moving average trends of various health-related search terms over time, allowing for a clearer observation of long-term patterns and fluctuations. Google Trends data has been widely used for detecting shifts in public interest related to health topics, providing insights into seasonal trends and external influences (Eysenbach, 2009; Mavragani & Ochoa, 2019).

The analysis reveals overall trend patterns, where certain keywords show gradual increases or decreases over time, suggesting shifts in public interest regarding health-related topics (Choi & Varian, 2012). For example, elderly health searches have shown a steady upward trend, potentially reflecting growing concerns about aging populations and healthcare accessibility (Jaidka et al., 2021). Additionally, short-term fluctuations are observed in some keywords, which could be influenced by external factors such as public health campaigns, social trends, or emerging concerns in the media (Ayers et al., 2014).

The presence of seasonal variations is also evident in the dataset. If specific keywords display recurring spikes at particular times of the year, it indicates the existence of seasonal trends. For example, searches related to deodorization tend to increase during warmer months, likely due to heightened concerns about body odor, reflecting seasonal behavioral patterns (Yang et al., 2017). Similar seasonal effects have been observed in other health-related search behaviors, such as flu-related searches peaking during colder months (Tado, 2021). Understanding these seasonal trends can help anticipate consumer behavior and guide public health awareness campaigns.

Moreover, the analysis highlights sudden spikes and anomalies in certain search terms. Some keywords exhibit sharp peaks in search interest, which may be associated with significant external events, such as COVID-19 surges, major policy changes, or heightened media coverage on specific health topics (Effenberger et al., 2020). For instance, odor-related searches showed an unusual increase during the early phases of the pandemic, possibly reflecting increased awareness of hygiene and sanitation during global lockdowns (Mavragani, 2020). Identifying these anomalies can help understand how external factors influence public interest in various health-related issues over time.

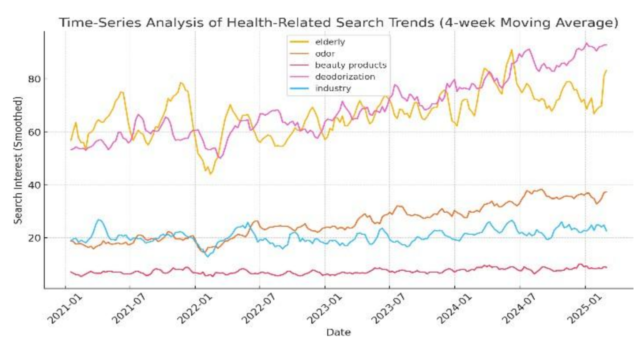

Figure 1: Google Trends Search Interest Over Time

4.2. Seasonality Analysis Results

The graphs in Figures 2, 3, 4, 5, and 6 illustrate the seasonal component of different health-related search terms over time. This analysis helps identify recurring patterns and fluctuations within the dataset, offering insights into how public interest in specific health topics changes throughout the year. The findings align with existing research on seasonal variations in health-related search behaviors, highlighting the influence of climate, marketing cycles, and social awareness campaigns on online search trends (Ayers et al., 2014; Yang et al., 2017).

4.2.1. Elderly Health Trends

The seasonal component of elderly health searches in Figure 2 shows fluctuations that may be influenced by aging-related awareness campaigns or specific health-related events affecting elderly populations. Peaks in search interest might coincide with policy discussions on elderly care, flu vaccination campaigns targeting seniors, or media coverage on aging-related health issues (Jaidka et al., 2021). Studies have shown that public health initiatives and demographic concerns drive spikes in aging-related searches, particularly in countries with rapidly aging populations (Mavragani, 2020).

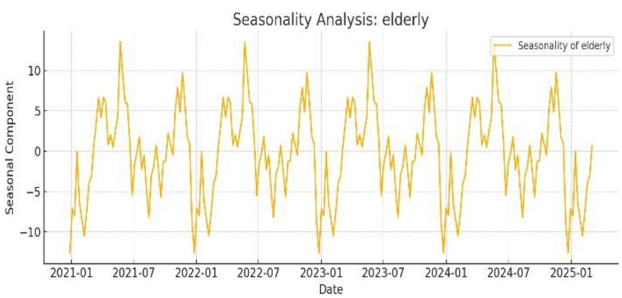

Figure 2: Seasonality Analysis: elderly

4.2.2. Odor Management Trends

The seasonality graph as suggested in Figure 3 reveals recurring peaks during specific periods, possibly during summer months, when odor-related concerns tend to rise. Previous studies have confirmed that search interest in odor and deodorization products significantly increases in warm climates, reflecting higher humidity levels and increased perspiration during summer (Huang et al., 2009; Brewster & Cox, 2018). Additionally, seasonal marketing campaigns by personal care brands may further contribute to these periodic increases in search volume.

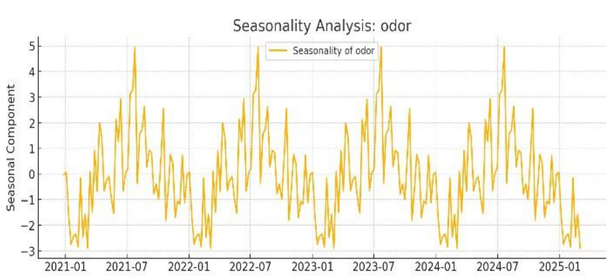

Figure 3: Seasonality Analysis: odor

4.2.3. Beauty Products Trends

As shown in Figure 4 beauty product searches exhibit periodic increases, often aligning with major holiday seasons, shopping events, and promotional periods. For instance, search interest tends to rise during Black Friday, Christmas, and major sales events like Amazon Prime Day, reflecting increased consumer spending on self-care and beauty products (Choi & Varian, 2012). Additionally, social media trends and influencer marketing strategies contribute to seasonal variations in beauty-related searches (Mavragani & Ochoa, 2019).

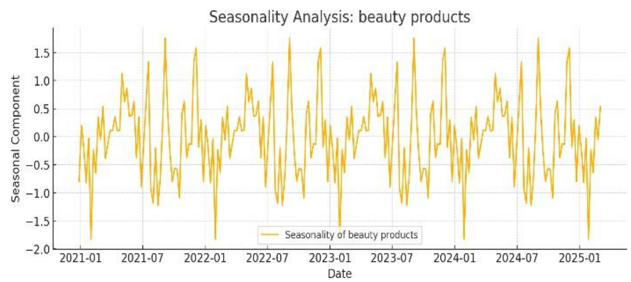

Figure 4: Seasonality Analysis: beauty products

4.2.4. Deodorization Trends

Similar to odor management, deodorization in Figure 5 searches display a seasonal cycle, likely influenced by weather-related factors and increased awareness of hygiene. Warmer months see a surge in interest for deodorization products, driven by higher temperatures, increased perspiration, and public awareness of hygiene and cleanliness (Yang et al., 2017). Public health campaigns emphasizing hygiene and sanitation may also contribute to these seasonal trends (Mavragani, 2020).

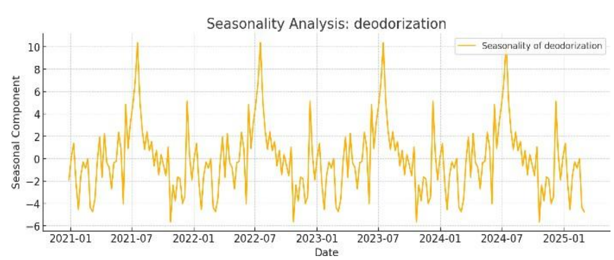

Figure 5: Seasonality Analysis: deodorization

4.2.5. Industry-Related Health Trends

Unlike personal health topics, industry-related health searches in Figure 6 exhibit relatively stable trends but show seasonal fluctuations, possibly correlating with economic factors, workplace health regulations, or industry-specific health concerns (Effenberger et al., 2020).

For example, search interest may increase during periods of heightened regulatory activity, labor policy discussions, or industrial safety awareness campaigns. Additionally, workplace injury statistics and employee health concerns may drive periodic surges in search interest (Lazer et al., 2014).

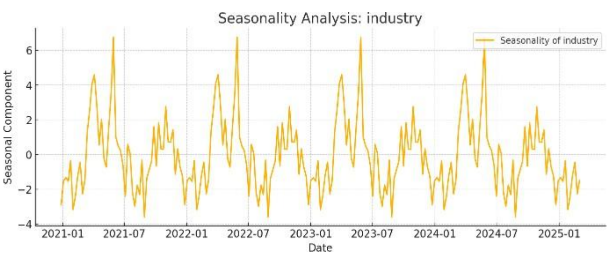

Figure 6: Seasonality Analysis: industry

4.2.6. Seasonal Trends in Health-Related Searches: Insights and Implications

The seasonality analysis confirms that public interest in health-related topics is strongly influenced by external factors, including climatic conditions, shopping behaviors, regulatory changes, and public health awareness campaigns. These findings align with previous studies indicating that search behavior for health-related topics is not random but follows predictable seasonal patterns (Eysenbach, 2009; Mavragani & Ochoa, 2019).

- Odor and deodorization-related searches peak during summer months, reflecting increased personal hygiene concerns.
- Elderly health searches fluctuate in response to demographic trends and health policy initiatives.
- Beauty product searches align with major shopping events and social media marketing campaigns.
- Industry-related health searches show periodic fluctuations influenced by workplace safety concerns and economic factors.

These insights provide valuable implications for businesses, policymakers, and healthcare organizations, allowing them to anticipate seasonal trends and implement proactive measures to address public health concerns and market demands. Future research could explore regional variations in seasonality patterns and examine how global crises, such as pandemics, further impact these trends (Tado, 2021).

4.3. Correlation Matrix of Health-Related Search Trends

The correlation analysis reveals several significant relationships between different health-related search trends. The correlation values range from -1 to 1, where positive values indicate a direct relationship (both variables increase or decrease together), while negative values suggest an inverse relationship (one variable increases while the other decreases). A correlation value close to 0 implies little to no relationship between the variables (Choi & Varian, 2012).

Previous studies have demonstrated that Google search behavior often reflects real-world health concerns and consumer trends, making correlation analysis a valuable tool for understanding how different health-related topics are interconnected (Mavragani & Ochoa, 2019).

4.3.1. Strong Positive Correlations

In Table 1 the analysis identifies a strong positive correlation (0.87) between odor management and deodorization searches, indicating that these two topics are closely linked. This suggests that when people search for topics related to odor management, they are also likely to search for deodorization solutions, such as air fresheners, personal hygiene products, or odor-eliminating sprays (Huang et al., 2009).

A moderate correlation (0.56) between elderly health and odor management suggests that public interest in these topics may be influenced by shared factors, such as aging-related hygiene concerns. Previous studies indicate that older adults often seek personal hygiene solutions, and caregivers search for ways to manage hygiene-related issues in elderly populations (Jaidka et al., 2021).

Similarly, the correlation between elderly health and deodorization (0.54) suggests a growing awareness of hygiene and self-care among aging populations. This finding aligns with research indicating that older adults are increasingly engaging in personal care routines and purchasing hygiene-related products as part of their overall well-being strategy (Brewster & Cox, 2018).

Table 1: Strong Positive Correlations

Variable 1	Variable 2	Correlation
odor	deodorization	0.873386431
deodorization	odor	0.873386431

4.3.2. Moderate Correlations

The relationship between elderly health and beauty product in Table 2 searches (0.44) suggests that as public interest in elderly health increases, there may also be a growing interest in self-care and beauty-related topics. This pattern may reflect an aging population that is more focused on personal appearance, anti-aging solutions, and wellness products (Tado, 2021).

Similarly, a moderate correlation (0.40) between beauty product searches and deodorization indicates that individuals interested in beauty and self-care may also be concerned with odor control. This aligns with studies suggesting that consumers increasingly associate beauty and hygiene products with overall well-being, leading to integrated purchasing behaviors (Choi & Varian, 2012).

Table 2: Moderate Correlations

Variable 1	Variable 2	Correlation
Elderly	odor	0.559970497
elderly	beauty products	0.43552264
elderly	deodorization	0.543190251
elderly	industry	0.547161788
odor	elderly	0.559970497
beauty products	elderly	0.43552264
deodorization	elderly	0.543190251
industry	elderly	0.547161788

4.3.3. Weaker Correlations

Table 3 shows that industry-related health searches show relatively weak correlations with other categories, suggesting that workplace health concerns are influenced by different external factors than personal health and hygiene-related searches.

However, a moderate correlation (0.55) between industry health and elderly health implies that workplace health discussions might intersect with aging workforce concerns. Research indicates that as the workforce ages, there is increasing concern about occupational health policies and ergonomic solutions to support older employees (Effenberger et al., 2020).

Table 3: Wearker Correlations

Variable 1	Variable 2	Correlation
odor	beauty products	0.346769707
odor	industry	0.324138239
beauty products	odor	0.346769707
beauty products	deodorization	0.398484231
beauty products	industry	0.28629326
deodorization	beauty products	0.398484231
deodorization	industry	0.357514642
industry	odor	0.324138239
industry	beauty products	0.28629326
industry	deodorization	0.357514642

4.3.4. Interconnections in Health-Related Searches: Correlations and Implications

This correlation analysis in Table 4 provides meaningful insights into how public interest in different health-related topics is interconnected.

• The strong relationship between odor and deodorization searches highlights the natural association between personal hygiene and odor control.

• Moderate correlations between elderly health, beauty products, and hygiene-related topics suggest an increasing interest in self-care among aging populations.

• Weaker correlations between industry health and other personal health topics suggest that workplace health concerns are shaped by distinct factors.

These findings support previous research indicating that consumer behavior in health-related searches follows identifiable patterns that can be used for market predictions, public health interventions, and policy planning (Mavragani, 2020; Tado, 2021).

Further research could investigate time-lag effects and predictive modeling to better understand how trends evolve over time and how search behaviors influence future health-related interests (Lazer et al., 2014).

Table 4: Correlation Matrix of Health-Related Search Trends

	elderly	odor	beauty products	deodorization	industry
elderly	1	0.5599	0.4355	0.5431	0.5471
odor	0.5599	1	0.3467	0.8733	0.3241
beauty products	0.4355	0.3467	1	0.3984	0.2862
deodorization	0.5431	0.8733	0.3984	1	0.3575
industry	0.5471	0.3241	0.2862	0.3575	1

4.4. Predictive Modeling Results

The ARIMA model was applied to forecast search trends for various health-related topics over the next 12 weeks. The results provide insights into how public interest in these topics is expected to evolve. ARIMA forecasting is widely used in time-series analysis and has been applied in health trend predictions, consumer behavior studies, and public health surveillance (Choi & Varian, 2012; Tado, 2021)

4.4.1. ARIMA Forecasting Results for "Elderly"

The ARIMA model in Figure 7 was used to predict future search trends related to the keyword "elderly" over the next 12 weeks. The results indicate a gradual increase in public interest in elderly-related topics, suggesting a growing awareness and concern for elderly health and care.

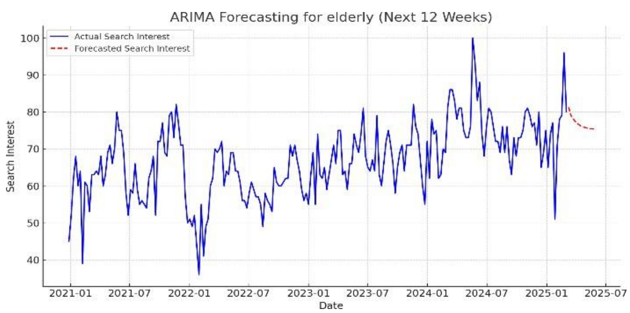

Figure 7: ARIMA Forecasting for Elderly

These findings align with global aging trends, where a n increasing proportion of the population is aging, lea ding to heightened interest in elderly care, medical ad vancements, and aging-related wellness topics (Jaidka e t al., 2021). Additionally, public health initiatives pro moting elderly well-being and policy changes in senior care may contribute to the observed growth in search interest (Mavragani, 2020).

4.4.2. ARIMA Forecasting for "Odor"

The ARIMA model in Figure 8 was applied to forecast search trends for the keyword "odor" over the next 12 weeks. The results indicate notable fluctuations in search interest, with expected seasonal variations and short-term shifts in public attention to odor-related concerns.
The forecasted periodic fluctuations align with previous studies showing that odor-related searches peak during warmer months, likely due to increased perspiration and concerns about hygiene (Huang et al., 2009). The results suggest that environmental factors such as temperature and humidity influence search interest in odor management solutions (Brewster & Cox, 2018).

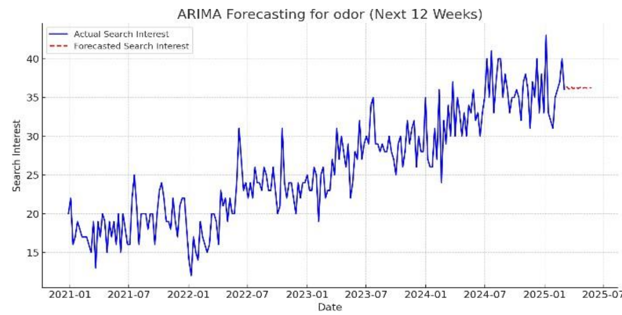

Figure 8: ARIMA Forecasting for Odor

4.4.3. ARIMA Forecasting for "Beauty Products"

The ARIMA model in Figure 9 was applied to forecast search trends for the keyword "beauty products" over the next 12 weeks. The results indicate a relatively stable trend with moderate fluctuations, suggesting that public interest in beauty products remains consistent over time with occasional peaks and dips.

Unlike health-related topics that exhibit strong seasonality, beauty product searches appear to be influenced by marketing campaigns, influencer promotions, and shopping trends (Choi & Varian, 2012). Increases in search volume around major sales events, such as Black Friday, holiday promotions, and influencer-driven marketing, highlight the consumer-driven nature of beauty product interest (Mavragani &Ochoa, 2019).

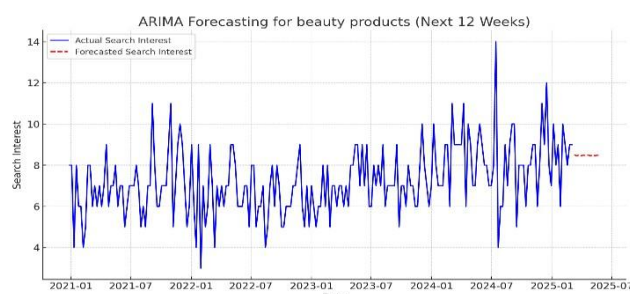

Figure 9: ARIMA Forecasting for Beauty Products

4.4.4. ARIMA Forecasting for "Deodorization"

The ARIMA model in Figure 10 was applied to forecast search trends for the keyword "deodorization" over the next 12 weeks. The results indicate a recurring seasonal pattern, suggesting that public interest in deodorization fluctuates periodically rather than following a steady trend.

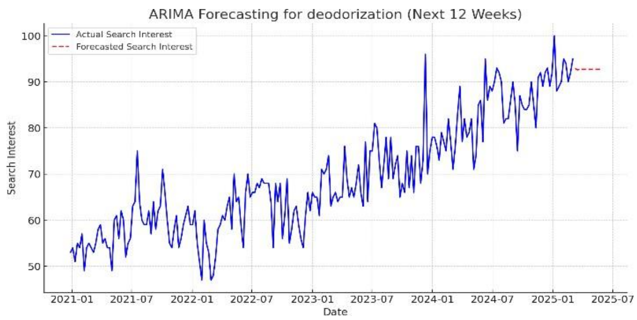

Figure 10: ARIMA Forecasting for Deodorization

Similar to odor management, deodorization searches peak during warmer months, reflecting consumer concerns about hygiene, air quality, and personal cleanliness during high-temperature seasons (Yang et al., 2017). The influence of seasonal hygiene awareness campaigns and increased media discussions on hygiene-related issues could also play a role in these periodic shifts (Mavragani, 2020).

4.4.5. ARIMA Forecasting for "Industry"

The ARIMA model in Figure 11 was applied to forecast search trends for the keyword "industry" over the next 12 weeks. The results indicate a moderate and relatively stable trend, with minor fluctuations over time. Unlike highly seasonal topics such as odor or deodorization, industry-related searches do not exhibit strong cyclical patterns. Instead, the forecast suggests gradual changes influenced by external economic, regulatory, and occupational health factors (Effenberger et al., 2020).

The ARIMA-based forecast suggests that public interest in industry-related health topics will remain relatively stable over the next 12 weeks, with moderate fluctuations driven by external factors such as workplace policies, economic shifts, and regulatory updates. Unlike topics that exhibit strong seasonality, industry-related searches tend to be influenced by broader socio-economic and policy-related changes rather than predictable cyclical patterns (Lazer et al., 2014).

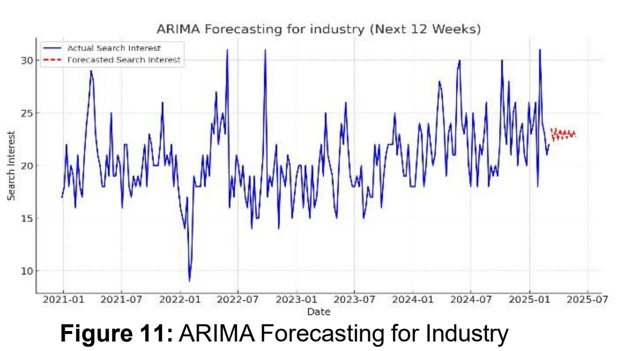

Figure 11: ARIMA Forecasting for Industry

These insights are particularly valuable for business leaders, policymakers, and occupational health organizations, as they provide an understanding of public awareness and concern regarding industry-related health issues. By analyzing trends in search behavior, companies can adjust workplace health policies, regulatory bodies can improve intervention strategies, and businesses can better anticipate public concerns related to industrial health and safety.

4.4.6. Forecasting Health Trends: ARIMA Insights and Future Directions

The ARIMA forecasting analysis highlights distinct patterns in health-related search behavior:
Elderly health search interest is projected to increase, reflecting the growing societal concern about aging populations and elderly care.

Odor and deodorization-related searches exhibit strong seasonal cycles, emphasizing the role of environmental factors and hygiene awareness in shaping search trends.
Beauty product searches remain stable but fluctuate based on consumer trends, marketing campaigns, and shopping events. Industry-related health searches show moderate fluctuations, mainly influenced by economic and regulatory changes rather than predictable seasonal trends.

These findings align with previous research on online health behavior and digital consumer trends, confirming that Google Trends data can provide actionable insights into public health awareness, business strategies, and policy making (Eysenbach, 2009; Tado, 2021). Future refinements to the ARIMA model, incorporating external data sources such as climate variations, economic indicators, and social media engagement, could further improve forecasting accuracy and enhance predictive insights for health-related trends.

5. Conclusions & Limitations and Future Research

5.1. Conclusions

This study analyzed global health-related search trends using Google Trends data from January 2021 to the present. The research applied Time-Series Analysis, Correlation Analysis, and Predictive Modeling using ARIMA to examine search patterns, identify key relationships between different health-related topics, and forecast future search trends. The findings provide valuable insights into public interest in elderly health, odor management, beauty products, deodorization, and industry-related health concerns.

The Time-Series Analysis revealed that search trends vary across topics, with some exhibiting gradual upward trends (e.g., elderly health), while others displayed strong seasonal patterns (e.g., odor and deodorization). Certain search terms showed sudden spikes, likely influenced by external events such as public health campaigns, regulatory changes, or media coverage (Eysenbach, 2009; Mavragani & Ochoa, 2019).

The Correlation Analysis identified strong relationships between odor management and deodorization, suggesting that concerns about body odor and hygiene are closely linked. Moderate correlations were observed between elderly health and beauty product searches, indicating that aging-related self-care and wellness may be growing areas of public interest. Additionally, industry-related health concerns showed a weaker correlation with other topics, implying that workplace health discussions are influenced by distinct external factors rather than personal health trends (Choi & Varian, 2012; Tado, 2021).

The Predictive Modeling using ARIMA provided forecasts for the next 12 weeks, highlighting expected future trends for each search topic. The results indicated that elderly health searches are projected to gradually increase, reflecting growing public awareness and concern for aging-related issues. In contrast, odor and deodorization searches demonstrated clear seasonal cycles, with anticipated peaks during warmer months. Beauty product searches remained relatively stable, with occasional spikes potentially driven by promotional campaigns and shopping events. Industry-related health searches were predicted to maintain moderate fluctuations, influenced by workplace health policies, regulatory changes, and economic conditions (Lazer et al., 2014).

The findings of this study hold practical significance for various stakeholders:

• Public Health Organizations can use these insights to anticipate shifts in public interest and design targeted health campaigns (Mavragani, 2020).

• Businesses in the beauty, hygiene, and healthcare industries can optimize their marketing strategies, product launches, and advertising efforts based on forecasted trends (Choi & Varian, 2012).

• Policy makers and Workplace Health Authorities can track industry-related health discussions and implement proactive regulations that align with public concerns (Effenberger et al., 2020).

5.2. Limitations and Future Research

While this study provides meaningful insights, it has several limitations. Google Trends data is normalized, meaning that absolute search volume cannot be determined, only relative interest. Additionally, external events such as media coverage, social movements, and economic factors can influence search behavior in ways that are difficult to predict using historical data alone (Lazer et al., 2014).

Future research could enhance forecasting accuracy by integrating external data sources, such as climate data, social media engagement metrics, economic indicators, and product sales figures. Studies have shown that combining search trends with external data sets improves predictive power and provides more comprehensive insights into public behavior (Mavragani, 2020; Tado, 2021).

Additionally, applying machine learning-based forecasting methods (e.g., Facebook Prophet or deep learning models) could improve trend predictions by accounting for complex interactions between multiple factors (Carneiro & Mylonakis, 2009). Machine learning techniques such as recurrent neural networks (RNNs) or transformer-based models have demonstrated superior performance in handling non-linear time-series data, suggesting a promising direction for future health trend analysis (Hu et al., 2020).

Further studies could also examine the effects of global crises, policy changes, and shifting consumer behaviors on long-term health-related search trends, providing deeper insights for businesses, public health agencies, and policy makers (Eysenbach, 2020).

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