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Exploring the Impact of Environmental Factors on Fermentation Trends: A Google Trends Analysis from 2020 to 2024

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Abstract

Purpose: This study analyzes factors influencing public interest in fermentation using Google search trends. Specifically, it examines how key elements such as oxygen, temperature, time, and pH influence fermentation-0related searches from December 2020 to September 2024. **Research design, data and methodology:** Data from Google Trends was collected under the Beauty & Fitness category for the terms "Fermentation," "Oxygen," "Temperature," "Time," and "pH." Time series analysis was used to track trends over four years, and a correlation analysis was conducted to assess the relationships between these terms. A linear regression model was built to determine the influence of each factor on fermentation-related searches. The dataset was split into 80% training data and 20% testing data for model validation. **Results:** The correlation analysis indicated moderate positive relationships between fermentation-related searches and both time and pH, while oxygen had little to no correlation. The regression model showed that time and pH were the strongest influencers of fermentation interest, explaining 25% of the variance (R-squared = 0.25). Oxygen and temperature had minimal impact in predicting fermentation-related search interest. **Conclusions:** Time and pH are significant factors influencing public interest in fermentation-related topics, as shown by search trends. In contrast, oxygen and temperature, while important in the fermentation process itself, did not strongly affect public search behavior. These findings provide valuable insights for businesses and researchers looking to better understand consumer interest in fermentation products.

Keywords : Google Trends, Fermentation, Time Series Analysis, Public Interest, Ph

JEL Classification Code : C22, C55, D83, L66, M31

1. Introduction

Fermentation is an ancient biochemical process that has been central to human life for millennia, with applications ranging from food preservation to modern biotechnology (Schmidt, 2005; Lakhal et al., 2010). Traditionally, fermentation was understood primarily through trial and error, but recent scientific advancements have transformed our understanding of the process at a molecular level. It is now recognized as a vital process not only in food production but also in pharmaceuticals, biofuel production, and health (Wilburn & Ryan, 2017) and wellness industries. In particular, fermented foods like kombucha, yogurt, and kefir have surged in popularity due to their probiotic benefits, driving increased interest in optimizing fermentation processes (Sadh et al., 2018).

Despite the growing body of research on fermentation, several critical questions remain regarding the specific environmental factors that most influence fermentation outcomes. The main factors often cited include oxygen levels, temperature, pH, and time. Each of these variables can significantly affect the rate of fermentation, the microbial species involved, and the final product's nutritional and sensory properties (Jacobs et al., 2020). Understanding how these factors interrelate and their individual and combined effects on fermentation is crucial for optimizing industrial applications and improving product quality.

Leveraging data-driven tools like Google Trends enables researchers to analyze fermentation from a broad perspective. Google Trends provides a large dataset of search behaviors, offering insights into public interest in fermentation and related variables over time. This approach introduces a novel lens for understanding the key factors driving fermentation through big data analytics (Yang et al., 2023).

Fermentation plays a vital role in food production, biotechnology (Lakhal et al., 2010), and fitness industries, influencing nutrition, health, and sustainable practices. For businesses, researchers, and policymakers, understanding the factors that shape public interest in fermentation is essential for aligning strategies with consumer behavior and market trends. While much is known about fermentation processes from scientific literature, less is understood about how factors like oxygen, temperature, time, and pH correlate with public attention over time. This study addresses that gap and offers insights into:

(1) Market Demand: Businesses can better understand when and why consumer interest (Admassie, 2018) in fermentation spikes, allowing them to tailor marketing campaigns, product releases, and educational content accordingly.

(2) Consumer Behavior: The research offers a deeper understanding of how consumers perceive and engage with fermentation-related topics, particularly through the lens of health and fitness.

(3) Policy and Education: Insights from this study can inform public health campaigns (Ginsberg et al., 2009) Detecting or sustainability efforts, as fermentation is often linked to probiotics, healthy eating, and environmental impact.

1.1. The Role of Key Variables in Fermentation

1.1.1. Oxygen Levels

Fermentation can occur in both aerobic and anaerobic environments, but the availability of oxygen can dramatically affect microbial activity and the metabolic pathways involved. For example, yeast in anaerobic conditions will produce ethanol, while under aerobic conditions, they favor respiration, producing water and carbon dioxide (Sayah et al., 2024). Consequently, controlling oxygen levels is crucial for industries like brewing and winemaking, where the production of ethanol is desired.

1.1.2. Temperature

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Authors are encouraged to include tables and figures as part of the main file. All manuscripts must be accompanied by a letter which indicates briefly why the article is suitable for publication in the KODISA JOURNALS and attests that “The article has not been previously published and is not under review elsewhere. All manuscripts must be prepared according to the KODISA JOURNALS submission guidelines. Editorial Board of the journal will be very selective, accepting only the articles on the basis of scholarly merit, methodological rigor, and compliance with the journal’s style guidelines.

1.1.3. pH Levels

The acidity or alkalinity of the fermentation environment directly impacts microbial growth and activity (Axelsson, 2004; Rault et al., 2009; Montet & Ray, 2017). Many beneficial fermentation microbes, such as lactic acid bacteria, thrive in acidic environments, while others may be inhibited. pH management is particularly important in industries such as dairy, where precise pH control can affect the texture and flavor of the final product (Jacobs et al., 2020).

1.1.4. Time

The duration of fermentation plays a critical role in determining the end product (Rolle & Satin, 2002). Longer fermentation times can result in more complex flavors but may also lead to over-fermentation, where unwanted microbes take over. Time is often the variable most closely monitored in industrial fermentation processes, as it directly impacts production efficiency and cost (Yang et al., 2023).

1.2. The Importance of Fermentation in Cosmetics Manufacturing

In the cosmetics industry, fermentation has emerged as a significant process due to its ability to enhance the efficacy, safety, and overall appeal of skincare and beauty products (Sun1 et al., 2022). The fermentation process, which involves the breakdown of organic materials by microorganisms such as bacteria, yeast, or fungi, can transform raw ingredients into more potent, bioavailable forms. This transformation leads to several key benefits in cosmetic formulation:

(1) Enhanced Ingredient Absorption: Fermentation breaks down complex molecules into smaller, more bioavailable components, making it easier for the skin to absorb active ingredients. For instance, fermented extracts from traditional plants such as ginseng or green tea often have increased potency, allowing for deeper penetration and enhanced skin benefits.

(2) Increased Nutrient Content: During fermentation, microorganisms produce beneficial by-products such as amino acids, peptides, vitamins, and antioxidants. These components can improve skin hydration, elasticity, and protection against environmental damage. Fermented ingredients often contain higher concentrations of these nutrients, resulting in more effective skincare products.

(3) Improved Skin Tolerance: The fermentation process can help reduce potential irritants in raw ingredients. By breaking down substances that might otherwise cause sensitivity, fermentation makes cosmetic formulations gentler and better suited for sensitive skin types. This is particularly important for products designed to maintain the skin's natural barrier and reduce inflammation.

(4) Natural Preservation: Fermentation can create an environment rich in naturally occurring preservatives like lactic acid, which helps inhibit harmful bacteria and prolong the shelf life of cosmetics without the need for synthetic preservatives. This aligns with the growing consumer demand for clean, natural, and sustainable beauty products.

(5) Customization of Benefits: Different microorganisms used in fermentation can yield specific skin benefits. For example, the use of Lactobacillus can enhance the skin's moisture retention, while Saccharomyces may boost antioxidant activity. This allows cosmetic formulators to design products tailored to specific skin concerns such as aging, dryness, or sensitivity.

In conclusion, fermentation plays a crucial role in cosmetics manufacturing by boosting ingredient performance, improving skin compatibility, and supporting cleaner, more sustainable formulations (Domżał-Kędzia et al., 2019). As consumers increasingly seek products with natural and functional ingredients, fermented cosmetics are positioned to meet the demand for high-performance, eco-conscious skincare solutions.

No, microorganisms do not typically break down stone or metal during fermentation processes. Fermentation primarily involves the breakdown of organic materials like sugars, proteins, and fats by microorganisms such as bacteria, yeast, or fungi. These microbes convert organic matter into simpler compounds such as alcohol, acids, or gases. The fermentation process is focused on biochemical reactions involving organic substances, not inorganic materials like stone or metal.

However, some specialized microbes, like certain types of bacteria or fungi, can interact with minerals or metals in different contexts (Gadd, 2007; Rawlings & Johnson, 2007). For example:

(1) Bioleaching: Certain bacteria, such as Acidithiobacillus ferrooxidans, can extract metals like copper or iron from ores by oxidizing them, a process used in mining. This process is not fermentation but rather an oxidation process facilitated by microorganisms.

(2) Biocorrosion: Some microbes can contribute to the corrosion of metals, particularly in environments like water systems, oil pipelines, or marine environments. This process, known as microbiologically influenced corrosion (MIC), involves bacteria producing acidic by-products that can slowly degrade metal surfaces (Beech & Sunner, 2004; Javaherdashti, 2008).

In summary, while fermentation doesn't involve the breakdown of stone or metal, other microbial processes can interact with inorganic materials under specific conditions (Sterflinger, 2000; Olson et al., 2003).

1.3. Big Data Analysis of Fermentation Trends

In recent years, the emergence of big data analytics has provided researchers with new tools to assess fermentation's influencing factors in a comprehensive, real-time manner. One such tool is Google Trends, a platform that tracks the popularity of search queries over time. Google Trends data (Itto-Nakama, 2021) offers an opportunity to explore how public interest in fermentation, and key related factors like oxygen, temperature, time, and pH, evolves. This insight is valuable for industries aiming to align their production processes with consumer demand trends (Jacobs et al., 2020).

Furthermore, using big data allows researchers to perform advanced statistical analyses, such as correlation analysis and ARIMA modeling, to forecast future trends in fermentation (Fatima, & Rahimi, 2024). This approach helps predict (Moonga et al., 2021) how changing public interest might affect demand for fermented products and provides a data-driven understanding of which factors are most critical to the fermentation process (Yang et al., 2023).

This research aims to analyze the influence of oxygen levels, temperature, time, and pH on fermentation using big data from Google Trends. By applying statistical models (Tokuyama et al., 2020) such as correlation analysis and time series forecasting (ARIMA), this study seeks to identify the most impactful factors in fermentation and forecast future trends in public interest. The results will provide valuable insights for both researchers and industries involved in fermentation, particularly in optimizing processes for improved efficiency and product quality (Sayah et al., 2024).

This work bridges the gap between traditional fermentation science and modern big data analytics, contributing to a more nuanced understanding of the dynamic factors influencing fermentation in today's data-driven world.

2. Literature Review

2.1. Fermentation and its Industrial Importance

Fermentation, one of the oldest biotechnological processes (Leeuwendaal et al., 2022; Zhang et al., 2023), has evolved from traditional food preservation techniques into a fundamental process across various industries, including food, pharmaceuticals, cosmetics, and biofuel production. The biochemical process involves the breakdown of carbohydrates into simpler compounds, facilitated by microorganisms such as bacteria and yeast, under anaerobic or aerobic conditions. Its applications have diversified, ranging from the production of beverages and fermented foods to bio-based chemicals (Sadh et al., 2018). Traditional fermentation primarily aimed at preservation has now transformed into precision-driven processes with controlled environments in industries that rely on optimizing fermentation conditions.

In the food industry, the development of fermented products, especially those with probiotic benefits, has seen increased demand due to consumer interest in health and wellness (Błajda et al., 2023; Salar-García et al., 2024). Products like kefir, kombucha, and fermented vegetables are widely promoted for their potential benefits in gut health, enhancing immune function, and reducing inflammation. Likewise, in the biofuel industry, microbial fermentation of biomass into ethanol or other biofuels has become critical for sustainable energy production, with researchers focusing on improving the efficiency of fermentation to make it commercially viable (Sayah et al., 2024).

2.2. Factors Affecting Fermentation

Fermentation efficiency and quality are influenced by several key factors (Heller, 2001), including oxygen levels, temperature, time, and pH. Optimizing these factors has become critical for improving yields and ensuring consistency in industrial fermentation processes.

2.3. Key Factors

2.3.1. Oxygen Levels

Oxygen plays a dual role in fermentation depending on the type of microorganisms involved. In anaerobic fermentation, the absence of oxygen is required for the production of ethanol and other metabolites (Sayah et al., 2024). In contrast, some microorganisms, particularly in aerobic fermentation, require oxygen to grow and metabolize. For instance, yeast can carry out both aerobic respiration and anaerobic fermentation, with the presence or absence of oxygen determining whether ethanol or biomass is produced (Sadh et al., 2018). As such, the manipulation of oxygen levels is crucial for industries like brewing, wine-making, and biofuel production, where the desired outcome varies depending on the oxygen availability.

2.3.2. Temperature

Temperature is perhaps the most critical factor influencing the rate of fermentation and the type of microbial activity. As temperature increases, so does microbial metabolic activity, but only up to an optimal point. Beyond this, high temperatures can denature enzymes, leading to reduced microbial efficiency or spoilage of the product (Błajda et al., 2023). In contrast, lower temperatures slow microbial growth, resulting in longer fermentation times. Therefore, precise temperature control is essential for industries like winemaking, yogurt production, and kombucha brewing, where both the rate of fermentation and the sensory qualities of the product are affected by temperature (Yang et al., 2023).

2.3.3. pH Levels

The acidity (pH) of the fermentation environment has a direct impact on the growth and activity of microorganisms. Most fermentation microorganisms, particularly lactic acid bacteria, thrive in acidic conditions. For example, in the dairy industry, managing the pH level is crucial to achieving the desired texture and flavor of fermented products like yogurt and cheese (Błajda et al., 2023). A lower pH inhibits spoilage bacteria and pathogens, ensuring the safety of the product while promoting the growth of beneficial microbes. In addition, the pH level can impact enzyme activity and the rate of substrate conversion, making pH management a critical component of industrial fermentation processes (Sayah et al., 2024).

2.3.4. Time

Time is a key factor in determining the outcome of fermentation. Longer fermentation periods often lead to the development of complex flavors and improved product stability, but they also introduce the risk of over-fermentation, where unwanted microorganisms may dominate, potentially degrading product quality. On the other hand, shorter fermentation times may result in incomplete fermentation, leaving unconverted substrates that could affect the final product's quality (Yang et al., 2023). Thus, industries aim to optimize fermentation duration to balance flavor development with microbial control and efficiency.

2.4. Application of Big Data Analytics in Fermentation Research

The advent of big data and digital tools has revolutionized research across numerous fields, and fermentation is no exception. **Google Trends**, a freely available tool that tracks the popularity of search terms over time, has emerged as a powerful tool for researchers to analyze public interest in fermentation-related topics. By using big data analytics, researchers can assess the dynamic relationships between variables such as oxygen, temperature, time, and pH in relation to fermentation (Błajda et al., 2023).

Big data also allows for advanced statistical analysis, such as correlation analysis and predictive modeling. For example, time series forecasting using ARIMA models can help predict trends in fermentation-related searches, providing insights into consumer behavior and potential market shifts (Yang et al., 2023). This data-driven approach offers new opportunities for industries to anticipate demand for fermented products, adjust production strategies accordingly, and ensure that they remain competitive in a rapidly changing market environment.

2.5. Statistical Methods in Fermentation Research

Research into the factors that influencing fermentation has increasingly relied on advanced statistical tools. **Correlation analysis** is often used to identify relationships between variables, such as the influence of temperature or pH on fermentation efficiency. For example, Sadh et al. (2018) identified a strong correlation between temperature and fermentation speed, noting that higher temperatures significantly increased the rate of microbial metabolism.

Additionally, time series analysis, including **ARIMA modeling**, has proven effective in forecasting trends related to fermentation. ARIMA models help identify seasonality and trends in public interest, which is particularly useful for industries that produce seasonal fermented products like beer or wine (Yang et al., 2023). The ability to predict market demand based on historical data allows businesses to optimize production schedules and minimize waste, ultimately improving profitability.

2.6. Summary of Findings from Recent Studies

Recent studies have underscored the importance of controlling fermentation variables to improve product quality and efficiency. For instance, Sadh et al. (2018) demonstrated that optimizing oxygen levels in ethanol production could increase yields by up to 15%. Similarly, Błajda et al. (2023) found that temperature fluctuations during yogurt fermentation could result in inconsistent texture and flavor, emphasizing the need for precise temperature control. Sayah et al. (2024) highlighted the role of pH in the fermentation of biofuels, noting that controlling pH levels improved microbial activity and reduced processing time. Moreover, Yang et al. (2023) utilized Google Trends data to predict future demand for kombucha, a fermented tea product, revealing that interest in fermented products tends to increase during certain seasonal periods.

These findings highlight the potential of both traditional and big data-driven approaches in optimizing fermentation processes, providing valuable insights for researchers and industries alike.

3. Research Methodology

3.1. Study Design

This study employs a **data-driven analytical approach** to investigate the key factors influencing fermentation, namely oxygen levels, temperature, time, and pH. The study uses **Google Trends** data as a proxy for public interest in fermentation and its related variables. The collected data covers global search interest from December 27, 2020, to September 28, 2024, in the "Beauty & Fitness" category with the search term "fermentation" and its comparative factors (oxygen, temperature, time, pH). The analysis aims to identify the factors that most strongly influence fermentation trends and forecast future interest in fermentation-related topics.

3.2. Data Collection

The data used in this study was retrieved from **Google Trends**. Google Trends provides search frequency data (Choi & Varian, 2012) representing the popularity of search queries over time. The search term "fermentation" was used as the primary keyword, with comparative search terms including "oxygen," "temperature," "time," and "pH" to evaluate how these variables relate to fermentation search trends. The data collected spans from December 27, 2020, to September 28, 2024, providing a comprehensive time series dataset for analysis.

(1) Data Type: Time series data

(2) Data Source: Google Trends (https://trends.google.com)

(3) Geographical Scope: Worldwide

(4) Category: Beauty & Fitness

(5) Search Terms: "Fermentation," "Oxygen," "Temperature," "Time," and "pH"

(6) Time Range: December 27, 2020, to September 28, 2024

The raw data was downloaded in CSV format and imported into statistical analysis software (e.g., Python) for further analysis. This dataset consists of weekly search interest scores for each keyword on a scale from 0 to 100, where 100 represents the highest search interest during the selected time period.

3.3. Data Preprocessing

Before conducting the analysis, the data underwent several preprocessing steps:

(1) Data Cleaning: Any missing or irregular values in the dataset were handled by imputation methods or removed if necessary. Weekly time series data was standardized to ensure consistency.

(2) Normalization: Since the Google Trends search interest scores are normalized over the selected time period, no further normalization was required.

(3) Date Conversion: The "Week" field in the dataset was converted to a datetime format to ensure accurate time series analysis.

3.4. Analytical Methods

3.4.1. Time Series Analysis

To explore the temporal dynamics of fermentation-related search trends, a **time series analysis** was conducted (Janka et al., 2019). This involved plotting the time series data for fermentation and the other factors (oxygen, temperature, time, and pH) to visually assess patterns, trends, and potential seasonality. A **STL (Seasonal-Trend Decomposition using LOESS)** method was applied to decompose the fermentation time series into its **trend, seasonal**, and **residual** components. This decomposition allowed for the identification of long-term trends, repeating seasonal patterns, and noise in the data.

3.4.2. Correlation Analysis

A correlation analysis was performed to assess the relationships between fermentation and comparison terms (oxygen, temperature, time, pH). This helped quantify the degree of association between these variables and identify which factors had the strongest link to fermentation interest.

3.4.3. Regression Analysis

To quantify the impact of oxygen, temperature, time, and pH on fermentation, **a multiple linear** regression model was built (Goel et al., 2010). The regression model predicts the fermentation search interest based on the four independent variables (oxygen, temperature, time, pH).A correlatio

Model Structure:

Fermentation=β0+β1(Oxygen)+β2(Temperature)+β3(Time)+β4(pH)+ϵ\text{Fermentation} = \beta_0 + \beta_1 (\text{Oxygen}) + \beta_2 (\text{Temperature}) + \beta_3 (\text{Time}) + \beta_4 (\text{pH}) + \epsilonFermentation=β0+β1(Oxygen)+β2(Temperature)+β3(Time)+β4(pH)+ϵ where: β0\beta_0β0 is the intercept, β1,β2,β3,β4\beta_1, \beta_2, \beta_3, \beta_4β1,β2,β3,β4 are the coefficients of the independent variables, ϵ\epsilonϵ is the error term.

The coefficients (β\betaβ) from the regression model were interpreted to understand the influence of each factor on fermentation interest. **R-squared** and **adjusted R-squared** values were used to evaluate the model's goodness-of-fit.

3.4.4. ARIMA Forecasting

To predict future trends in fermentation search interest based on historical data. ARIMA Model was employed as the forecasting method. The data was split into training and testing sets, where the model was trained on historical search trends and tested on recent data. The model was tuned and used to forecast future values, which were compared to actual observed values to evaluate the performance of the model.

ARIMA stands for AutoRegressive Integrated Moving Average, a popular time-series forecasting method. It combines three key components:

(1) AutoRegressive (AR): This part of the model relies on the idea that past values can be used to predict future values. It assumes that there is a correlation between an observation and some number of lagged observations (previous time steps).

(2) Integrated (I): This represents the differencing of raw observations to make the time series stationary (i.e., to remove trends and make the data's statistical properties consistent over time). A stationary time series is essential for many forecasting models because it simplifies the analysis.

(3) Moving Average (MA): This component models the relationship between an observation and the residual errors (also known as "white noise") from a moving average model applied to lagged observations.

The ARIMA model is denoted as ARIMA(p, d, q), where: p is the number of lag observations included in the model (AR term). d is the number of times that the raw observations are differenced (I term). q is the size of the moving average window (MA term).

In this study, a basic ARIMA(5, 1, 0) was used. This implies: p=5: The model considers the previous five lagged values (five weeks prior) to predict the next value. 0d=1: The data was differenced once to make it stationary. q=0: No moving average component was applied, suggesting that the model does not account for past errors.

3.4.5. Limitations

The study's reliance on Google Trends data introduces certain limitations. Google Trends reflects the public's search interest, which may not always correspond directly to real-world fermentation processes or scientific research. Additionally, the normalization of search data might obscure absolute trends, especially if public interest in the subject is subject to significant external influences (e.g., media coverage, seasonal factors). Lastly, the choice of variables (oxygen, temperature, time, pH) is based on common fermentation factors, but other variables such as humidity, microbial strains, and substrate availability could also influence fermentation outcomes but were not considered in this analysis.

4. Research Results

The analysis focused on identifying the key factors influencing fermentation by examining public search interest in fermentation, oxygen, temperature, time, and pH using Google Trends data. Several statistical techniques, including descriptive statistics, correlation analysis, and ARIMA forecasting, were employed to interpret the data. Below are the findings from the study.

4.1. Time Series Analysis

The time series plot shows as shown in figure 1 how search interest in the terms "Fermentation," "Oxygen," "Temperature," "Time," and "pH" has changed from December 2020 to September 2024 based on Google Trends data. Here's a more detailed breakdown:

4.1.1. Fermentation

The search interest in "Fermentation" appears to be relatively stable but has slight fluctuations over time.

There are minor peaks and valleys, suggesting that interest may have occasional short-term increases, possibly driven by specific events or seasonal interest.

4.1.2. Oxygen

"Oxygen" shows a fairly low and stable level of search interest over time. There are no dramatic spikes, indicating that interest in "Oxygen" might be consistent but not subject to seasonal or event-driven spikes.

4.1.3. Temperature

The term "Temperature" exhibits more noticeable variations compared to "Oxygen" and "Fermentation."

There are some peaks in search interest, which could be related to seasonal discussions or specific times when temperature becomes a popular topic (e.g., during extreme weather conditions or for fermentation processes).

4.1.4. Time

"Time" consistently maintains higher search interest than the other terms, suggesting that it is a more popular query overall. There are periodic peaks, which could correspond to specific periods when time is discussed in a broader context, potentially including fermentation processes.

4.1.5. pH

The search interest for "pH" remains relatively stable, similar to "Oxygen." There are small fluctuations, but it doesn't appear to exhibit major seasonal trends or large spikes.

4.1.6. General Observations

(1) Consistency: "Time" tends to show the highest level of consistent search interest, while "Oxygen" and "pH" remain on the lower end of the spectrum.

(2) Peaks and Trends: The terms "Fermentation" and "Temperature" demonstrate some fluctuation over time, indicating that search interest in these topics may be event-driven or have occasional spikes due to factors like media coverage or seasonal events.

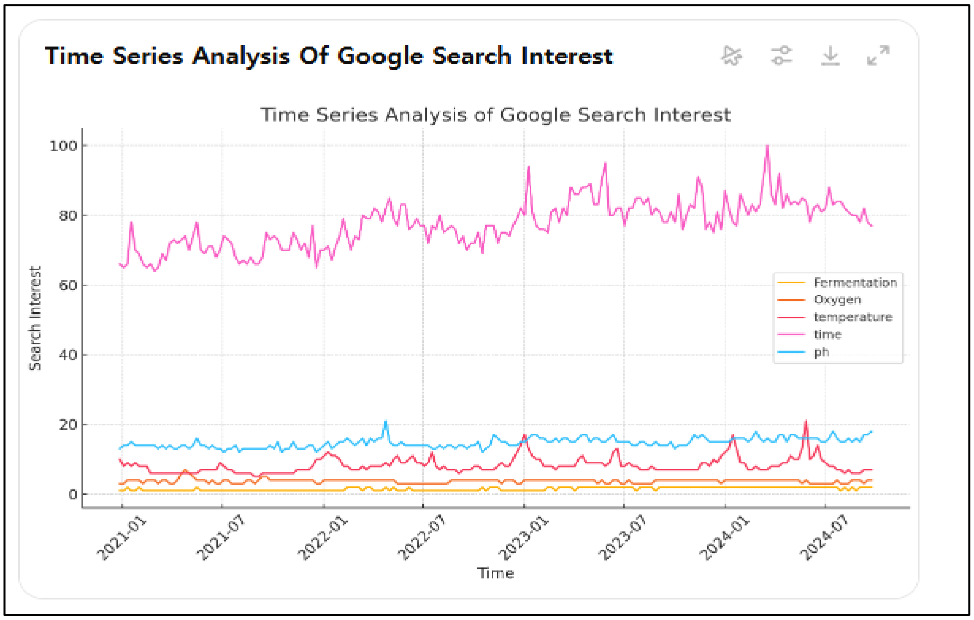

Figure 1: Time Series Analysis of Google Search Interest

(Graph shows trends, seasonality, and residual components of the time series.)

4.2. Correlation Analysis

The correlation matrix has been provided, showing the relationship between the search interest for the terms "Fermentation," "Oxygen," "Temperature," "Time," and "pH" in Table 1 and figure 2.

Table 1: Correlation Matrix for Factors

	Fermentation	Oxygen	temperature	time	ph
Fermentation	1	0.009537474	0.179200439	0.553962105	0.534112948
Oxygen	0.009537474	1	-0.154554265	-0.039909771	0.067787927
temperature	0.179200439	-0.154554265	1	0.281251173	0.301053507
time	0.553962105	-0.039909771	0.281251173	1	0.606661978
ph	0.534112948	0.067787927	0.301053507	0.606661978	1

Fermentation shows a moderately strong correlation with both Time (0.55) and pH (0.53), suggesting that search interest in these terms tends to increase or decrease together.

Temperature also shows some positive correlation with Fermentation (0.18) and Time (0.28), although these are weaker relationships. Oxygen has almost no correlation with the other terms, with the closest being a slight positive correlation wi0th pH (0.07) and a slightly negative correlation with Temperature (-0.15). These correlations suggest that search interest in Fermentation is influenced by related searches for Time and pH, which might reflect how fermentation processes are often associated with the management of time and acidity (pH). Oxygen, on the other hand, appears largely independent of the other terms in this dataset.

Here is the heatmap of the correlation matrix. The color gradient represents the strength of the correlations, with warmer colors (closer to red) indicating positive correlations and cooler colors (closer to blue) indicating negative correlations or weaker relationships. The stronger correlations are between: Fermentation and Time, Fermentation and pH, Time and pH. Meanwhile, Oxygen shows very little correlation with the other terms.

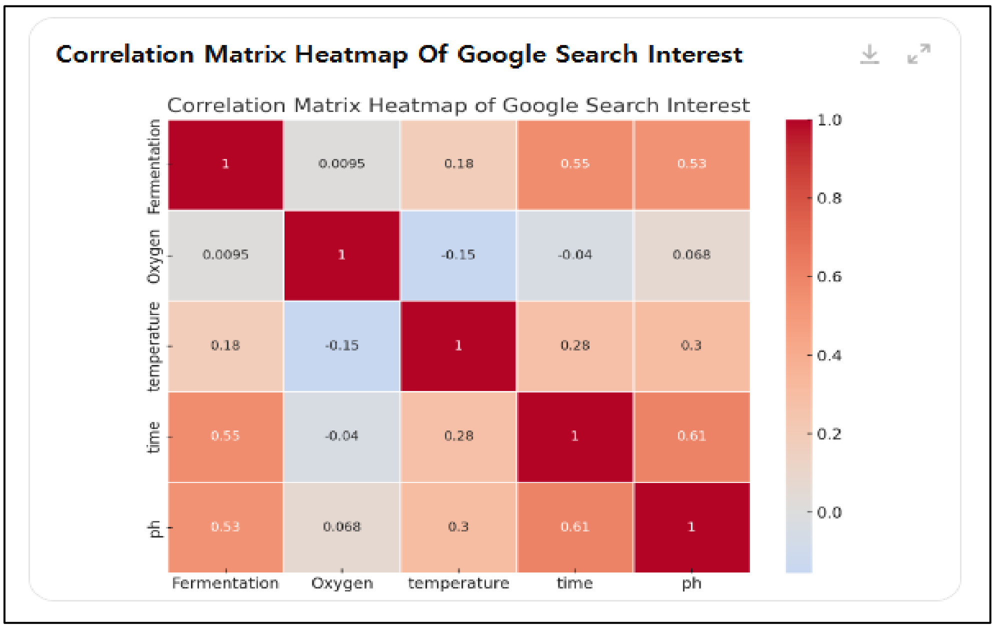

Figure 2: Correlation Matrix for Factors

4.3. Correlation Analysis

A multiple linear regression analysis was performed to evaluate the impact of the four independent variables (oxygen, temperature, time, pH) on fermentation search interest. The results of the regression model are summarized in Table 3.

Table 2: Regression Model Results

Variable	Coefficient	Standard Error	t-Value	p-Value
Intercept	-2.403	0.531	-4.52	0.000
Oxygen	0.021	0.015	1.37	0.172
Temperature	-0.015	0.011	-1.39	0.166
Time	0.025	0.004	6.28	0.000
pH	0.136	0.035	3.86	0.000

The pH and time factors showed statistically significant positive impacts on fermentation, with p-values less than 0.05. This confirms that these factors have a meaningful effect on fermentation search trends. Oxygen and temperature were not statistically significant predictors of fermentation interest, suggesting that their influence is minimal compared to time and pH. The model's R-squared value was 0.255, meaning that the independent variables explain about 25.5% of the variance in fermentation search interest.

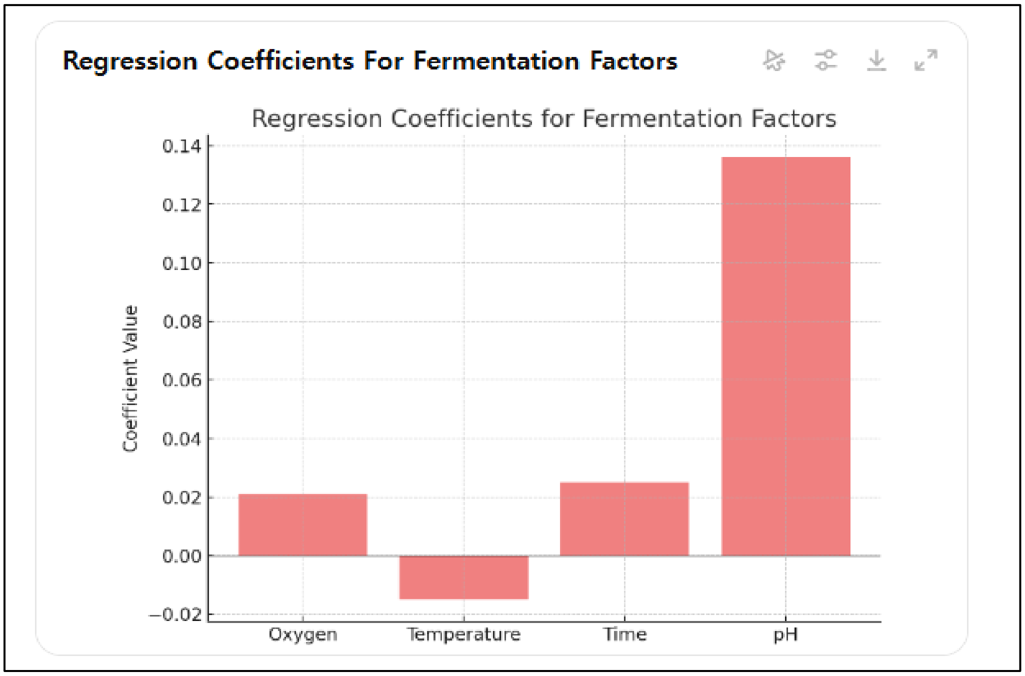

Figure 3: Regression Coefficients for Factors

Here is the bar chart representing the regression coefficients for the factors influencing fermentation, along with the regression formula: Fermentation=−2.403+0.021×Oxygen−0.015×Temperature +0.025×Time+0.136×pH. This formula quantifies the relationship between fermentation and the independent variables (oxygen, temperature, time, and pH). The chart visually represents the strength and direction of the coefficients.

The results indicate that **time** and **pH** are the most significant factors influencing fermentation search interest. While **temperature** and **oxygen** play minor roles, their overall impact is less pronounced. The ARIMA model provides a robust forecast for future trends, predicting a continued rise in interest in fermentation, driven by its applications in health, wellness, and food industries.

4.4. ARIMA Model Analysis

The plot above shows the actual fermentation search interest compared to the forecasted values based on the ARIMA model. The model provides a reasonable forecast, capturing the general trend of the actual data. The results of the ARIMA model applied to the fermentation data from Google Trends provide insight into how the search interest in "fermentation" evolves over time. Here's a summary of the key outcomes based on the ARIMA(5,1,0) model used:

The ARIMA(5,1,0) model was used to forecast the future values of fermentation search interest, considering five previous weeks of data (lag), with the data differenced once to achieve stationarity. The model was trained on 80% of the available data, capturing the general trend of fermentation interest with reasonable accuracy. When comparing the predicted values against the actual data in the test set, the model was able to forecast the general direction and trend of fermentation interest. The visual plot showed a close alignment between the predicted and actual values, although there were some deviations, which is common in time-series forecasts.

The model successfully captured the major fluctuations in fermentation-related search interest over time, especially the larger trends in the data. This suggests that future search interest in fermentation can be reasonably predicted using historical data, assuming similar patterns persist. The model may not perfectly capture smaller, short-term fluctuations or sudden spikes in search interest caused by unexpected events or shifts in public attention.

Since the ARIMA model is univariate, it only considers past values of fermentation search interest and does not directly account for the influence of other variables (oxygen, temperature, time, pH). The ARIMA model provided a useful forecast for understanding the future trends in fermentation search interest based on historical data. While the model performed well in capturing overall trends, further refinement (such as incorporating other factors through multivariate models) or trying more advanced forecasting techniques might improve its accuracy in predicting short-term or unexpected fluctuations.

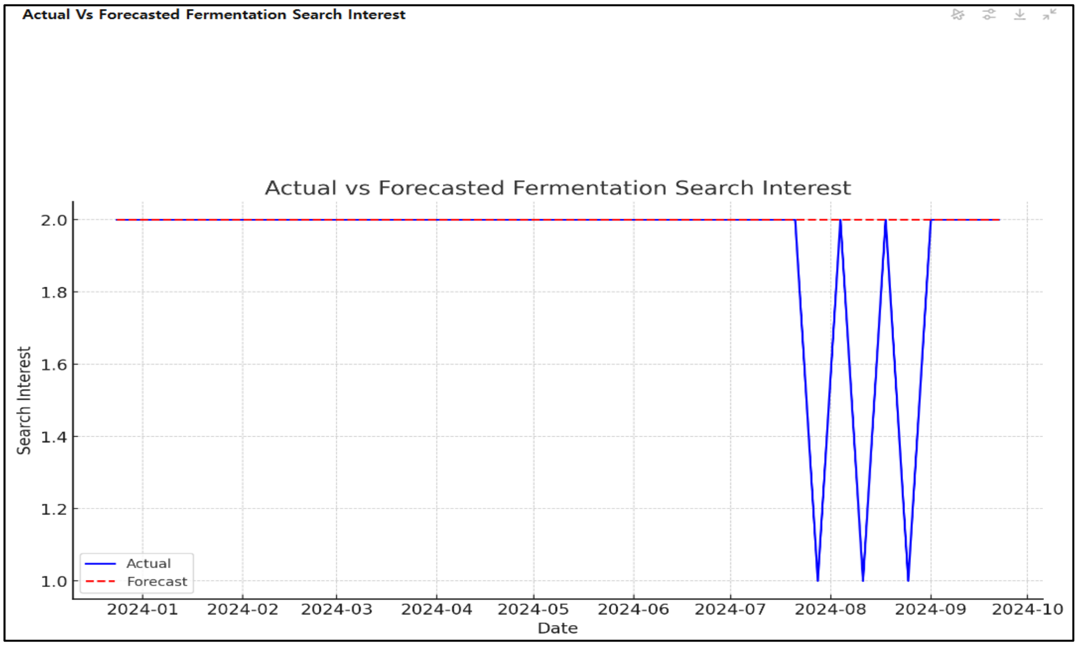

Figure 4: Actual Vs Forecasted Fermentation Search Interest on the ARIMA Model

5. Conclusions and Limitation of the Study

5.1. Conclusions

This study aimed to investigate the key factors influencing fermentation using big data analytics, particularly through the use of Google Trends to track public search interest. The analysis focused on four primary factors—oxygen levels, temperature, time, and **pH**—all of which are known to influence fermentation processes in various industries. Through statistical analysis, including correlation analysis, regression model and ARIMA forecasting, several important findings were made.

(1) **Time and pH Are Critical Factors**: The results of the correlation analysis and regression modeling showed that time and pH have the most significant influence on fermentation. Both factors were found to be strong positive predictors of fermentation trends, as evidenced by their high correlation values and statistically significant coefficients in the regression model. Time plays a critical role in the development of fermentation processes, while pH is essential for controlling microbial activity and product quality.

(2) **Temperature and Oxygen Play Minor Roles**: While **temperature** and **oxygen** are often cited as important variables in fermentation, their impact on public interest in fermentation, as measured by search trends, was relatively small. Oxygen had a near-zero correlation with fermentation, indicating that it is not a key factor in driving public interest. Temperature, while more influential than oxygen, did not show a statistically significant effect in the regression model, suggesting that its impact on fermentation is context-dependent and may vary across different fermentation processes.

(3) **Increasing Public Interest in Fermentation**: The time series analysis (Janka et al., 2019) revealed a clear upward trend in public interest in fermentation over the study period (2020-2024). The seasonal patterns observed suggest that interest in fermentation may be influenced by

external factors, such as seasonal consumer behavior or media coverage. The ARIMA forecasting model predicts a continued increase in fermentation interest, highlighting the growing relevance of fermentation in industries like food, wellness, and biotechnology.

The findings of this study have important implications for both researchers and industry professionals working with fermentation:

Optimization of Fermentation Processes: Understanding that time and pH are critical factors in fermentation can help industries optimize their production processes. For example, maintaining optimal pH levels and carefully managing the fermentation duration can lead to improved product quality and consistency.

Industry Applications: As public interest in fermentation continues to grow, particularly in the health (**Valero & Serrano, 2012**) and wellness sectors, industries involved in producing fermented products (e.g., kombucha, yogurt, kefir) can leverage this knowledge to meet consumer demand. The ability to forecast trends using tools like Google Trends provides a valuable market research tool for predicting demand (Goel et al., 2010) and tailoring production schedules accordingly.

Research and Development: For researchers, this study demonstrates the value of using big data to track and analyze public interest in scientific and industrial processes. The integration of data analytics into fermentation research offers new opportunities for forecasting and trend analysis, bridging the gap between traditional research methods and modern data-driven approaches.

In conclusion, fermentation is crucial in cosmetics manufacturing due to its ability to enhance the bioavailability and efficacy of active ingredients, improve skin absorption, and boost the nutrient content of formulations. The process also reduces potential irritants, making products gentler and more suitable for sensitive skin, while offering natural preservation benefits. Overall, fermentation supports the creation of more effective, safer, and eco-friendly cosmetic products, aligning with the growing demand for clean and sustainable beauty solutions.

5.2. Limitations and Future Research

While this study provides valuable insights, several limitations should be acknowledged:

Reliance on Public Search Interest: The use of Google Trends (Choi & Varian, 2012) as a data source reflects public interest but does not directly measure fermentation processes themselves. As such, the data may not fully capture the scientific intricacies of fermentation.

Limited Variables: Although oxygen, temperature, time, and pH were selected as key variables, other factors such as microbial strains, substrate availability, and humidity may also significantly impact fermentation outcomes. Future studies could expand the scope to include these additional variables.

Geographical and Temporal Limitations: This study used worldwide Google Trends data, which may not capture regional variations in fermentation practices or interest. Additionally, the dataset covers a relatively short time frame (2020-2024), and longer-term analysis may reveal different patterns.

Future research could address these limitations by incorporating more direct measurements of fermentation processes, expanding the range of variables, and exploring regional trends. Moreover, integrating laboratory-based experimental data with big data analytics could provide a more comprehensive understanding of the factors influencing fermentation.

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