Web search trends on fibromyalgia: development of a machine learning model

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Abstract

Objectives

Fibromyalgia (FM) is a chronic pain condition characterised by widespread musculoskeletal pain, fatigue, and cognitive dysfunction. The growing reliance on the internet for health-related information has transformed how individuals seek medical knowledge, particularly for complex conditions like FM. This study aimed to analyse online search behaviours related to FM across multiple countries, identify temporal trends, and assess machine learning models for predicting search interest.

Methods

Google Trends data (2020–2024) were analysed across sixteen countries. Time-series analysis, linear regression, and the Mann-Kendall trend test assessed monotonic trends, while seasonal decomposition identified periodic fluctuations. An Auto-Regressive Integrated Moving Average (ARIMA) model forecasted search volumes for 2025. Machine learning models, including Random Forest (RF) and Extreme Gradient Boosting (XGBoost), were used to predict search trends, with feature importance evaluated using SHAP (Shapley Additive Explanations) values.

Results

Search interest in FM varied across countries, with China, the UK, the USA and Canada showing the highest engagement, while Peru, Spain and Turkey had the lowest. Brazil, Italy and the UK exhibited rising search trends, whereas Argentina, Canada, Greece and the USA showed declines. Seasonal analysis revealed mid-year peaks in Brazil and Italy, while Turkey saw late autumn increases. ARIMA forecasting predicted stable or increasing trends in Brazil, Canada and Mexico, while Germany and Venezuela showed slight declines. Machine learning analysis identified short-term search history (search volumes from the previous day, week, and month) as the most influential predictor.

Conclusions

Understanding online search behaviour can enhance FM education. Targeted awareness campaigns and improved digital health literacy initiatives could sustain engagement and improve patient knowledge. Future efforts should focus on optimising online health resources and integrating evidence-based decision aids.

Key words

fibromyalgia, online search behaviour, chronic pain, Google trends analysis, predictive modelling, machine learning

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Received on April 26, 2025; accepted in revised form on May 19, 2025.

Competing interests: none declared.

Introduction

Fibromyalgia (FM) is a chronic and complex condition with an unknown aetiology, affecting approximately 2-7% of the general population (1). It is classified as nociplastic pain, which results from altered functioning of pain-related sensory pathways within the nervous system, leading to heightened pain sensitivity and central sensitisation (2). Clinically, FM is characterised by widespread musculoskeletal pain, fatigue, mood disturbances such as anxiety and depression, and disrupted sleep patterns, all of which significantly impair quality of life (3).

The exact mechanisms underlying fibromyalgia remain unclear, but the condition is thought to involve dysregulation of central and peripheral pain modulation pathways, leading to hyperalgesia (4). Research suggests that genetic predisposition plays a role, along with several triggering factors, including physical inactivity, obesity, chronic stress, and environmental influences (1, 5, 6).

Notably, certain viral and bacterial infections have been linked to FM onset (7). Another potential mechanism involves the pathogenetic role of anti-satellite glial cell (SGC) IgG antibodies. Studies have shown that these antibodies can bind to the dorsal root ganglia, suggesting a direct impact on sensory processing and pain modulation (8). Moreover, research indicates that FM symptoms can be transferred from humans to mice through the administration of these anti-SGC IgG antibodies (9). FM patients who carry these antibodies tend to exhibit a more severe disease phenotype, suggesting that this immune-mediated mechanism may contribute to disease progression and symptom intensity (9). Additionally, small fiber neuropathy (SFN) has been identified in a significant subset of FM patients, suggesting a potential overlap between these conditions (10). Moreover, FM frequently coexists with rheumatic diseases such as rheumatoid arthritis, osteoarthritis, lupus, and ankylosing spondylitis, further complicating its clinical presentation (11).

The increasing reliance on the Internet for health-related information has transformed the way patients engage with their medical conditions (12). In fact, millions of individuals worldwide search for health information online daily, often exceeding the number of visits to healthcare providers (13). This digital behaviour is particularly relevant for chronic diseases where many patients turn to online sources to better understand their diagnosis, seek treatment options, or explore lifestyle modifications that may alleviate their symptoms (14).

Given the lack of definitive biomarkers for FM and the challenges associated with its clinical management, online searches could be useful as an important tool for patients looking to supplement the information provided by healthcare professionals. The accessibility of online resources also enables individuals with FM to connect with peer communities, fostering support and shared experiences that can be critical for managing a chronic illness (15). Social media platforms have also emerged as a major source of health-related information, particularly for individuals managing chronic diseases (16). However, the reliability of online medical content remains a significant challenge, particularly for individuals with low health literacy who may have difficulty distinguishing credible sources from misinformation. Therefore, gaining insights into how individuals utilise web searches is crucial for improving scientifically validated public education. Enhancing digital health literacy and integrating evidence-based decision aids into health-related websites can help ensure that users access accurate and reliable medical information.

The objective of this study was to examine online search behaviours related to FM across multiple countries. Additionally, the study aimed to identify the most frequently searched associated queries, providing insights into public interest, concerns, and informational needs regarding FM on a global scale.

Methods

Search strategy and data collection

This study analysed internet search trends related to FM over five years

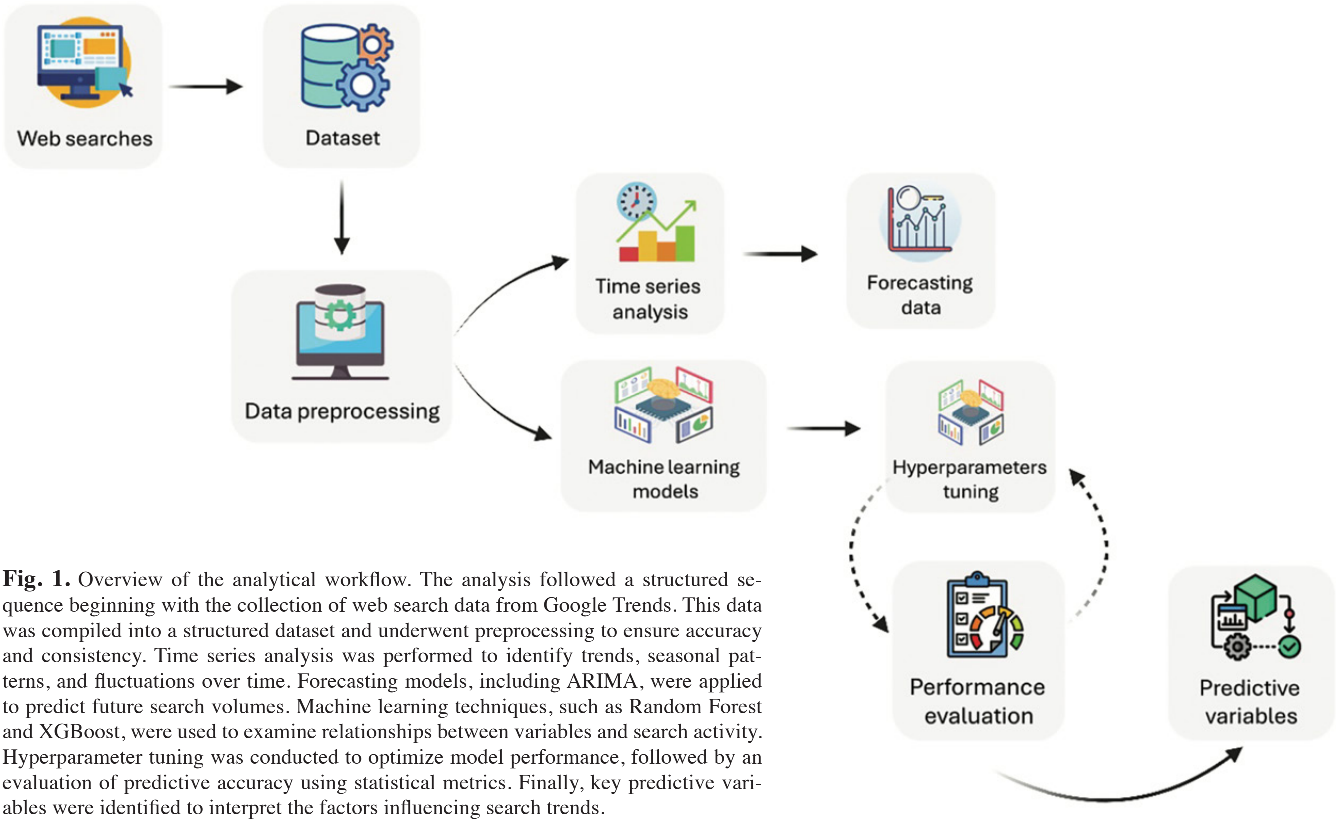

Fig. 1. Overview of the analytical workflow. The analysis followed a structured sequence beginning with the collection of web search data from Google Trends. This data was compiled into a structured dataset and underwent preprocessing to ensure accuracy and consistency. Time series analysis was performed to identify trends, seasonal patterns, and fluctuations over time. Forecasting models, including ARIMA, were applied to predict future search volumes. Machine learning techniques, such as Random Forest and XGBoost, were used to examine relationships between variables and search activity. Hyperparameter tuning was conducted to optimize model performance, followed by an evaluation of predictive accuracy using statistical metrics. Finally, key predictive variables were identified to interpret the factors influencing search trends.

(2020-2024) using Google Trends data (https://trends.google.com). The analysis focused on sixteen countries (Argentina, Brazil, Canada, China, Colombia, France, Germany, Greece, Italy, Mexico, Peru, Spain, Turkey, the United Kingdom, the United States and Venezuela) chosen as representative regions across the Americas, Europe and Asia. These countries were selected to provide a comprehensive overview of global online search behaviours related to FM, capturing geographic and cultural variations in public interest and informational needs. Weekly search volumes for "fibromyalgia" were recorded from January 1, 2020, to December 31, 2024. Search terms were translated into the native languages of each country (*Argentina, Brazil, Colombia, Italy, Mexico, Peru, Spain and Venezuela: Fibromialgia; Canada, USA, UK: fibromyalgia; China:英语; France and Germany: Fibromyalgie; Greece: ινομυαλγια; Turkey: Fibromiyalji*) using Google Translate and subsequently validated for linguistic and cultural accuracy by native-speaking people with relevant cultural knowledge to reduce the risk of semantic discrepancies in search term. Google Trends was used to obtain relative search volume (RSV) data, normalized to a scale of 0 to 100. This approach enabled the analysis of search behaviour across different regions and time periods, providing insights into temporal and geographical trends in public interest related to fibromyalgia.

Data processing and analysis

The temporal trends in weekly internet search volumes were assessed for each country using linear regression. The presence of a monotonic trend was evaluated using the Mann-Kendall test, which detects consistent increases or decreases over time without requiring normality assumptions. To enhance cross-country comparisons, the search volume data for each country were adjusted by removing the baseline intercept (17), thereby normalising country-specific variations and emphasizing deviations from historical search patterns. To further understand the structure of the dataset, time-series decomposition was applied, breaking down search volume data into trend, seasonal, and residual components (18). The decomposition was performed separately for each country using Seasonal and Trend Decomposition (STL) (19), a robust non-parametric method that effectively handles non-stationary data and outliers by applying LOESS smoothing (20). For predictive modelling, an Auto-Regressive Integrated Moving Average (ARIMA) model (21) was trained to generate 12-month forecasts with confidence intervals. To identify potential predictive variables associated with search volumes, machine learning models, including Random Forest (RF) (22) and Gradient Boosting (XGBoost) (23), were employed. The dataset was split into training (80%) and testing (20%) sets to evaluate model generalisation. The predictive models were fine-tuned using grid search hyperparameter optimization, where the number of randomly selected predictors per split (mtry) was optimised via 5-fold cross-validation to enhance accuracy and prevent overfitting (24). The importance of predictive variables was assessed using SHAP (SHapley Additive Explanations) (25), which quantifies the contribution of each feature to the model's predictions,

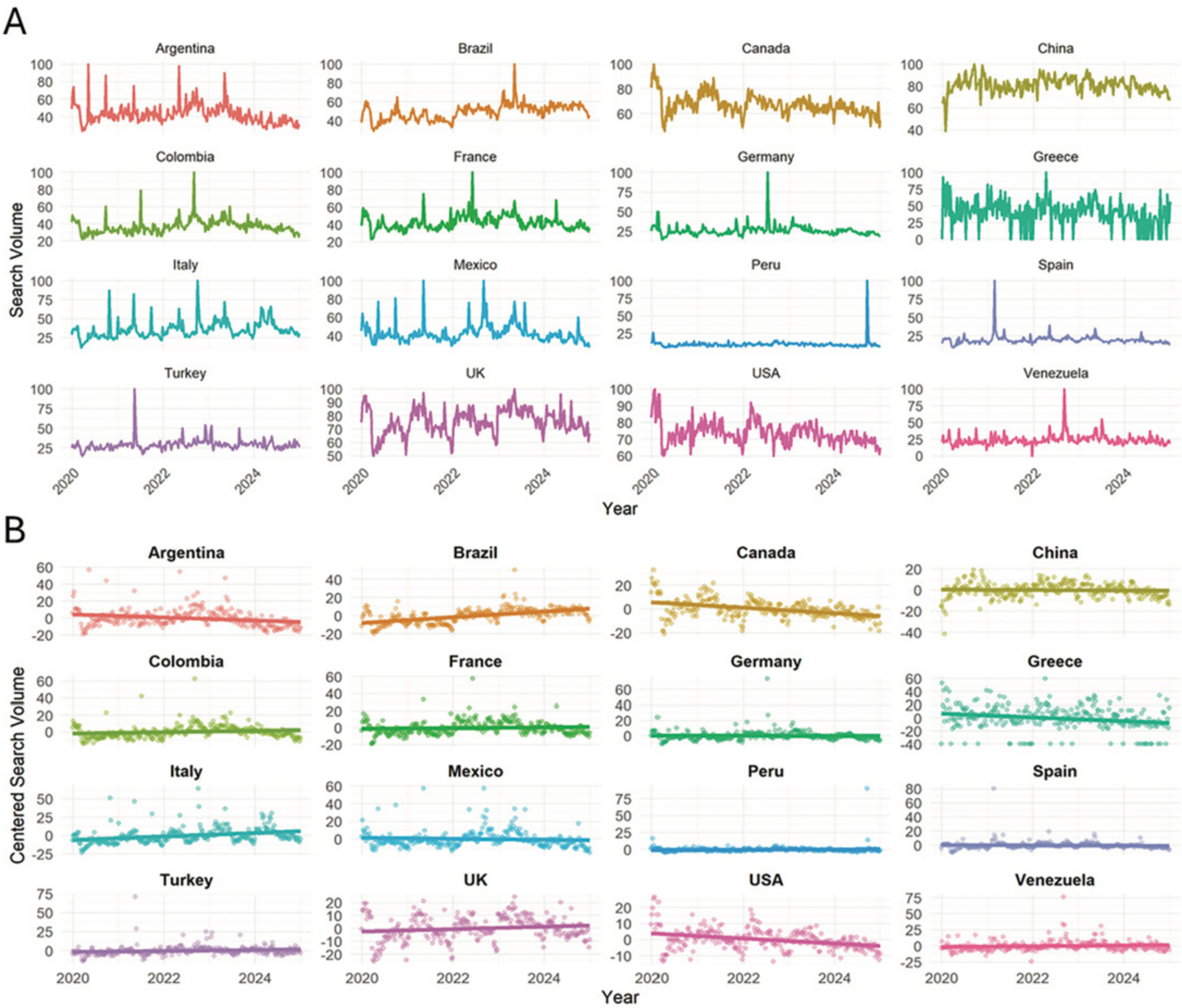

Fig. 2. Search Volume Trends and Regression Analysis. A) Weekly search activity for the term "fibromyalgia" across sixteen countries (Argentina, Brazil, Canada, China, Colombia, France, Germany, Greece, Italy, Mexico, Peru, Spain, Turkey, UK, USA, Venezuela) over a five-year period. Each panel displays the temporal progression of raw search data for a specific country, with search volumes normalized on a scale from 0 to 100, relative to the highest recorded search peak. B) Linear regression analysis of search volume trends from 2020 to 2024. The regression lines illustrate the overall trend in search activity for each country, with individual points representing weekly data fluctuations.

offering greater interpretability compared to traditional feature importance methods (26). Additionally, Partial Dependence Plots (PDPs) (27) were generated to visualie the marginal effect of key predictors (*e.g.*, lagged time-dependent variables) on the predicted search volume. Lagged features are a feature engineering method designed to reflect temporal dependencies and trends within time series data. This approach involves shifting the time series data by a specified number of time intervals, commonly known as the lag or time delay (28). Model performance was evaluated using multiple error metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Bias Error (MBE) (29). All analyses were conducted in R software v4.3.2 (R Foundation for Statistical Computing, Vienna, Austria, www.r-project.org), with visualisation and model interpretation facilitated by the DALEX, fastshap, iml, and pdp packages. The sequential steps of the analysis are schematically summarised in Figure 1.

Results

A total of 4192 data points, with 262 from each country, were included in the analysis. Google Trends data were analysed based on weekly search activity recorded over a five-year period, offering an in-depth perspective on search volume trends for each country. The unprocessed data, illustrated in Figure 2A, depict the fluctuations and temporal patterns in search activity across the sixteen countries. Regression analysis further highlighted specific temporal trends, as demonstrated in Figure 2B.

Among the analysed countries, Brazil and Italy exhibited statistically significant positive slopes (0.00869, $p<0.001$ and 0.00662, $p<0.001$, respectively), indicating a rising trend in search vol-

Table I. Linear regression model results for the trends in online search interest for fibromyalgia across 16 countries.

Country	Slope	95% CI	*p*
Argentina	-0.00494	-0.00740 to -0.00248	<0.001
Brazil	0.00869	0.00705 to 0.0103	<0.001
Canada	-0.00629	-0.00797 to -0.00461	<0.001
China	-0.000620	-0.00230 to 0.00106	0.47
Colombia	0.00236	0.000498 to 0.00421	0.013
France	0.00120	-0.000754 to 0.00315	0.23
Germany	-0.000255	-0.00182 to 0.00130	0.75
Greece	-0.00803	-0.0123 to -0.00373	<0.001
Italy	0.00662	0.00413 to 0.00911	<0.001
Mexico	-0.00146	-0.00379 to 0.000868	0.22
Peru	0.000691	-0.000707 to 0.00209	0.33
Spain	-0.000664	-0.00212 to 0.000791	0.37
Turkey	0.00185	0.000254 to 0.00345	0.023
UK	0.00261	0.000429 to 0.00479	0.019
USA	-0.00428	-0.00569 to -0.00287	<0.001
Venezuela	0.00157	-0.000368 to 0.00351	0.11

umes over time. Similarly, Colombia, Turkey and the UK also demonstrated significant upward trends (p=0.013, p=0.023 and p=0.019, respectively), though with smaller slope values. Conversely, Argentina, Canada, Greece and the USA showed statistically significant negative slopes (-0.00494, -0.00629, -0.00803, and -0.00428, respectively, all p<0.001), reflecting a consistent decline in search volumes. In contrast, countries such as China, France, Germany, Mexico, Peru, Spain and Venezuela did not exhibit statistically significant trends (p>0.05), indicating relatively stable search activity over the observed period (Table I).

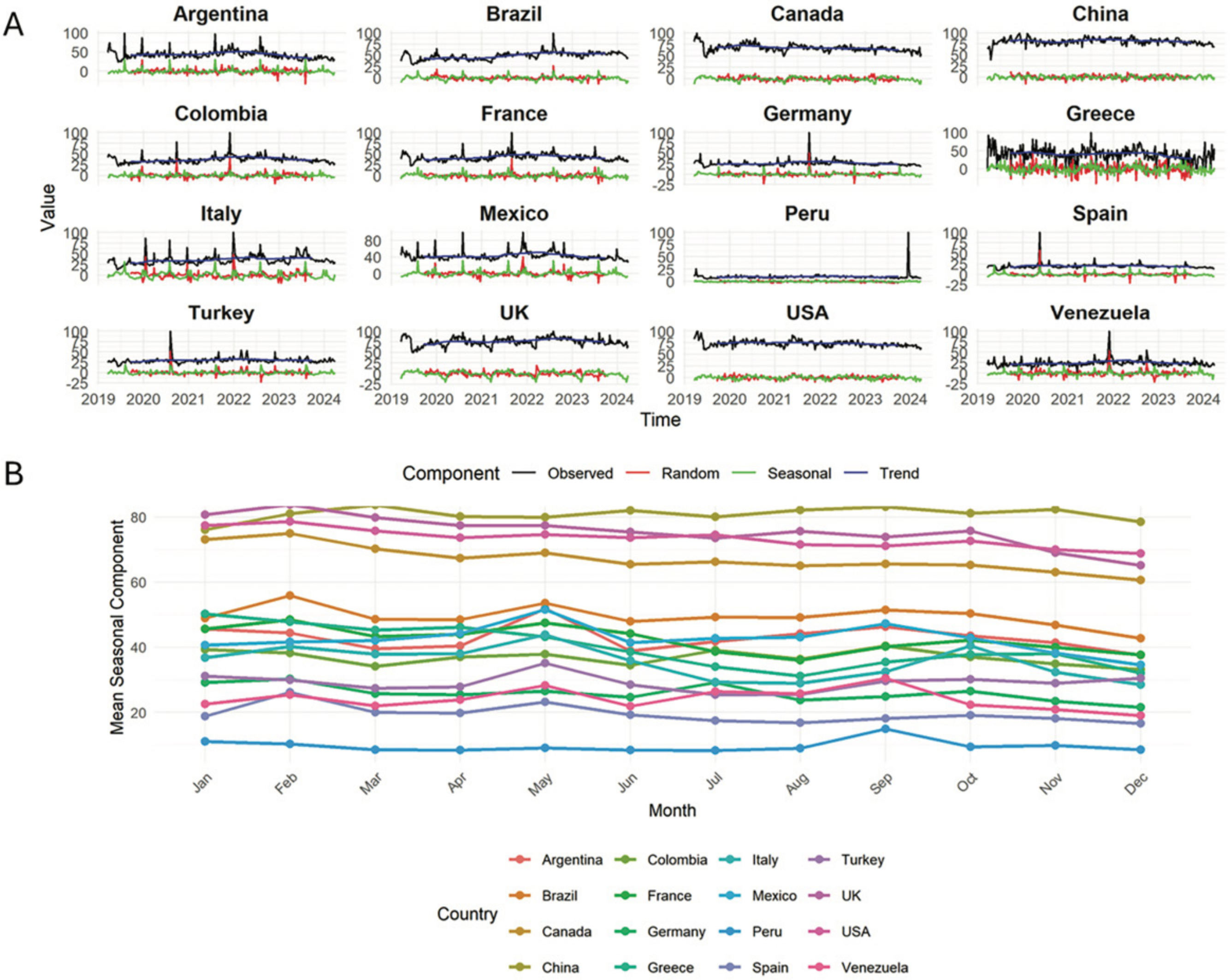

Fig. 3. Seasonal decomposition and trends in search volumes for FM across 16 Countries.
A) Time-series decomposition of search volumes for FM across Argentina, Brazil, Canada, China, Colombia, France, Germany, Greece, Italy, Mexico, Peru, Spain, Turkey, the UK, the USA, and Venezuela. The observed data (black), trend component (blue), seasonal fluctuations (green), and residual variations (red) are displayed for the five-year period (2019–2024). B) Mean seasonal components across months, illustrating distinct seasonal trends and variations in search activity among the 16 countries, revealing differences in peak interest periods throughout the year.

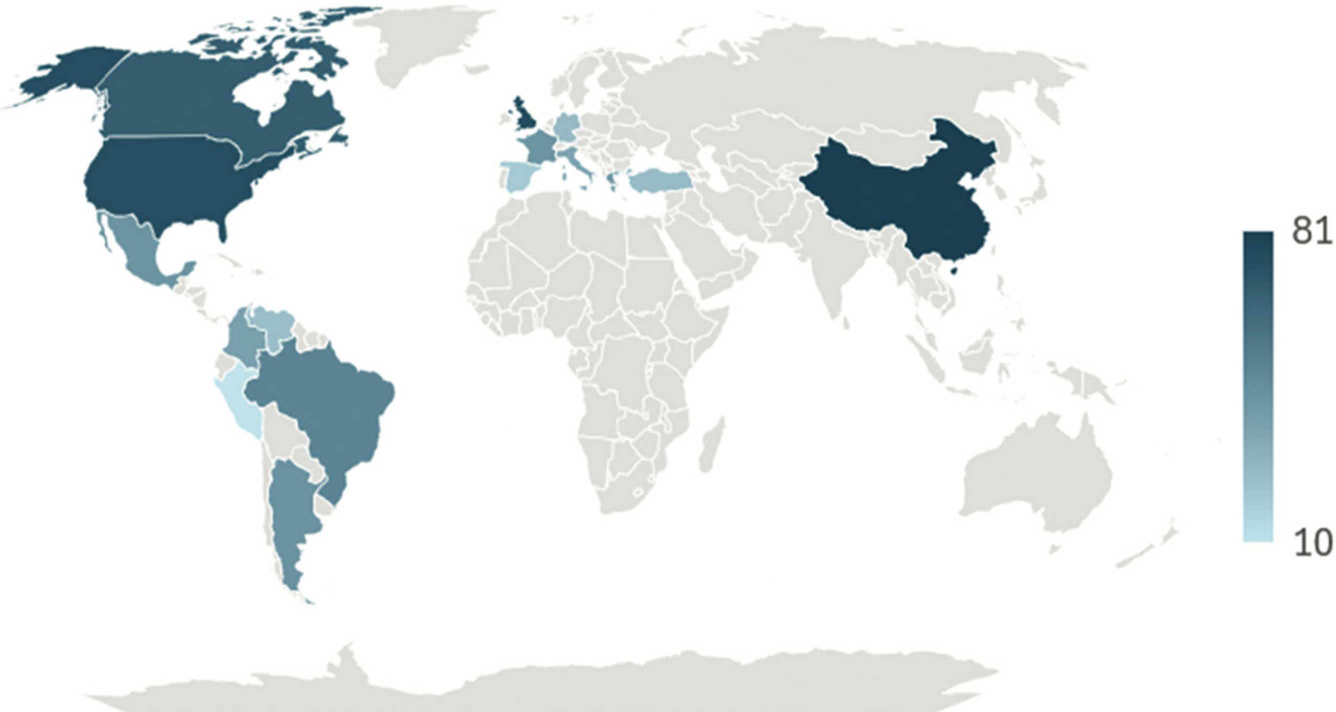

Fig. 4. Global distribution of mean search volume over five years. The colour gradient represents the relative search intensity, with darker shades indicating higher search activity.

The Mann-Kendall trend test identified significant variations in online search interest for FM across the 16 countries analysed. Brazil, Canada, Italy and the USA exhibited highly significant trends over time ($p<0.001$). These suggest strong directional changes in search activity. Argentina, Colombia, Greece and Turkey also demonstrated statistically significant trends, though with slightly higher p-values ($p<0.001$ to $p=0.01$). Conversely, China, France, Germany, Mexico, Peru, Spain and the UK did not show significant trends ($p>0.05$), indicating relatively stable or fluctuating search volumes over the observed period (Fig. 3A). Seasonal decomposition analysis further revealed distinct patterns among countries (Fig. 3B). For instance, Italy and Brazil displayed consistent seasonal peaks in mid-year months, reflecting increased search interest during that period. In contrast, Germany and Spain exhibited relatively stable seasonal fluctuations, while Turkey showed pronounced peaks in late autumn. The UK experienced minor variations, with a slight decline in early spring. The residual component, depicted in red (Fig. 3A), accounted for anomalies and deviations not explained by trend or seasonality, emphasising the presence of unexplained fluctuations in search behaviour. A detailed decomposition for each country is provided in Supplementary Figure 1.

The five-year mean search volume across sixteen countries (Fig. 4) ranged from 10 (Peru) to 81 (China), with China, the UK (76), the USA (74) and Canada (67.1) showing the highest interest. In contrast, Peru (10), Spain (19) and Turkey (25) had the lowest search volumes. South American countries like Brazil (49), Argentina (43) and Colombia (37) showed moderate engagement, while European nations varied, with France (42) and Greece (40) ranking higher than Germany (26) and Italy (35).

ARIMA-based forecasts for 2025 indicate varying trends in search volumes across the 16 countries analysed (Fig. 5). Search interest is expected to remain relatively stable in Argentina, France and Greece, while Brazil, Canada and Mexico are projected to experience an upward trend. Conversely, a slight decline is anticipated in Germany and Venezuela. The UK is forecasted to maintain the highest and most consistent search activity, with confidence interval values approaching 90, whereas Spain and Peru are predicted to sustain lower but steady search volumes throughout the year. In China, ARIMA-based projections for 2025 suggest a stable yet relatively high level of search interest, with forecasted values consistently ranging between 70 and 90 (Fig. 5).

The dataset, consisting of 4,192 search volume data points, was utilised to train RF and XGBoost models for predictive analysis. After model optimization, the RF model demonstrated stronger predictive performance compared to XGBoost, particularly in variance explanation and error minimisation (Table II). Specifically, the RF model exhibited robust predictive power with an R^2 of 0.92 for the training set and 0.56 for the testing set. While the model effectively captured variance in the training phase, its generalisation ability decreased when applied to unseen data. The prediction errors remained moderate, with RMSE values of 7.02 (training) and 14.66 (testing), and MAE values of 4.71 (training) and 10.07 (testing). The MBE was close to zero (0.03 in training and 0.49 in testing), suggesting minimal systematic bias

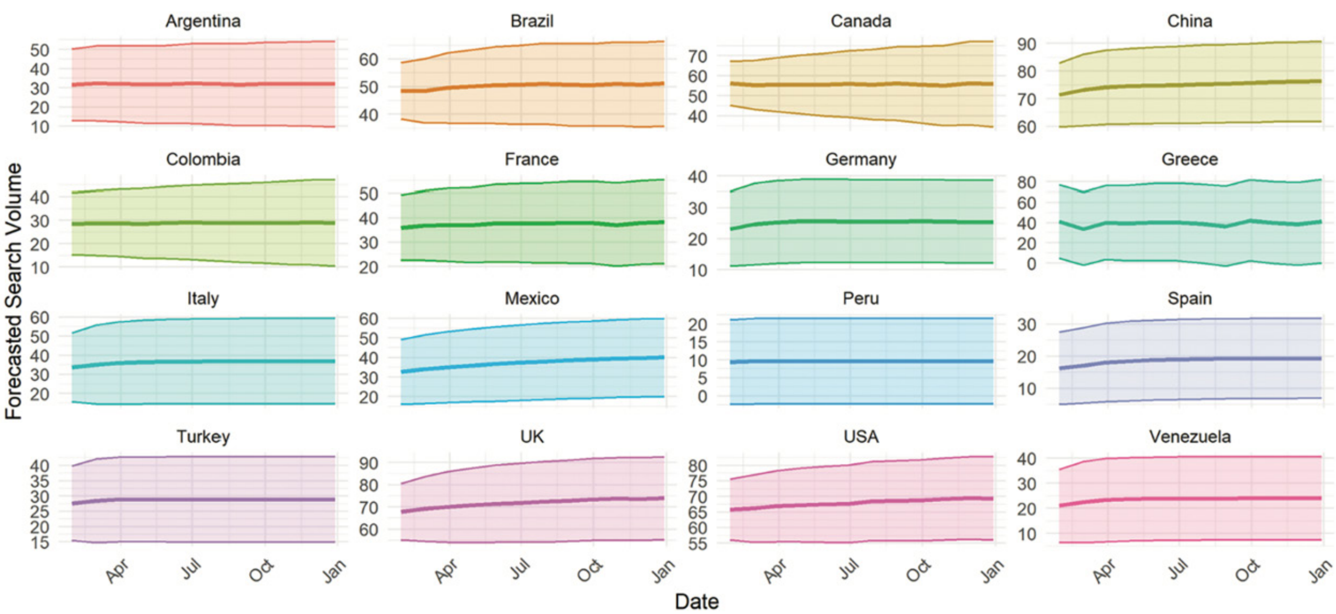

Fig. 5. Twelve-month forecast of search volumes by country. Each panel illustrates the projected search volumes (solid lines) for the next 12 months, for each country, along with the 95% confidence intervals (shaded areas), which represent the uncertainty of these predictions. The forecasts highlight anticipated trends in search activity in 2025.

Table II. Comparison of performance metrics for RF and XGBoost models across training and testing sets.

Metrics	RF (train)	RF (test)	XGBoost (train)	XGBoost (test)
R^2	0.92	0.56	0.99	0.48
RMSE	7.02	14.66	2.76	16.15
MAE	4.71	10.06	1.93	11.51
MBE	0.029	0.49	-0.0016	0.65

in predictions. In contrast, the XGBoost model displayed a higher R^2 of 0.99 in the training phase but a significantly reduced R^2 of 0.48 for the test set, indicating potential overfitting. The error metrics reflected this pattern, with RMSE values of 2.76 (training) and 16.15 (testing) and MAE values of 1.93 (training) and 11.51 (testing). The model's bias remained low for training (MBE=-0.0016), but a slightly higher bias was observed in the test set (MBE=0.65), suggesting less accurate generalisation. Consequently, the RF model achieved a better balance between predictive power and generalization, whereas XGBoost exhibited signs of overfitting, performing exceptionally well on the training data but struggling with test data. While both models provided valuable insights, RF demonstrated greater stability, making it the preferable choice for predicting search volume trends with lower error rates and more reliable real-world applicability.

The comparison between actual and predicted search volumes, modelled using the optimised RF algorithm, is presented in Figure 6 for each of the analysed countries.

The overall graphical assessment of the RF model's predictive accuracy is presented in Supplementary Figure 2. The feature importance analysis, conducted using SHAP values, provided critical insights into the most influential predictors within the optimised RF model. The results highlighted that temporal lag variables—Lag_1 (yesterday's search volume, SHAP: 2.81), Lag_7 (search volume 7 days ago, SHAP: 2.77), and Lag_30 (search volume 30 days ago, SHAP: 2.50)—had the highest impact on the model's predictive accuracy. Among them, Lag_1 emerged as the most significant predictor, indicating that the most recent search activity is the strongest determinant for forecasting future trends. Beyond lag features, broader temporal indicators such as Year (SHAP: 1.70) and Month (SHAP: 1.32) played a marginal role in capturing seasonal patterns, in fact their contribution was notably lower than that of short-term search volume lags. This SHAP analysis not only quantified feature importance but also provided interpretability by illustrating how each predictor influenced the model's decisions (Fig. 7). The dominance of Lag_1, Lag_7, and Lag_30 underscores the autoregressive nature of search behaviour, reaffirming that search volumes follow strong temporal dependencies. The Partial Dependence Plots (PDP) presented in Figure 8 illustrate the marginal impact of the most influential lagged variables (Lag_1, Lag_7, and Lag_30) on the predicted search volume while keeping all other features constant. The analysis revealed that Lag_1 has a strong positive relationship with predicted search volume, indicating that recent search activity is a critical determinant of future trends. In contrast, Lag_7 exhibits a non-linear effect, where initial increases in past search activity correspond to stable predictions, but a decline occurs when search volumes exceed a threshold, suggesting potential saturation effects. Similarly, Lag_30 displays periodic fluctuations, reinforcing the presence of potential saturation effects in search

Fig. 6. Predicted versus actual search volumes across countries. Comparison of observed (red) and predicted (blue) search volumes using the RF model across training and testing datasets. Each panel represents a different country, illustrating the model's ability to capture temporal trends and fluctuations in search interest over time. The alignment between actual and predicted values highlights the model's forecasting accuracy and generalization capacity.

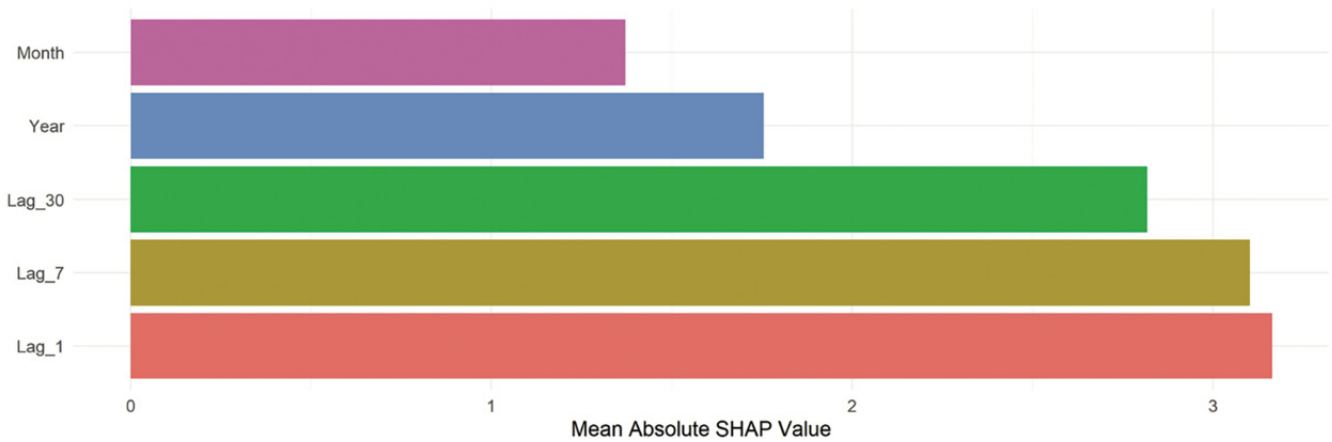

Fig. 7. SHAP feature importance for the optimized RF model. The most influential predictors were Lag_1 (yesterday's search volume), Lag_7 (search volume 7 days ago), and Lag_30 (search volume 30 days ago), highlighting the strong temporal dependency in search trends. The mean absolute SHAP values indicate the magnitude of each feature's impact on model predictions.

behaviour. These findings confirm the strong temporal dependency in search trends, emphasizing the importance of short-term historical data in forecasting future search interest.

The most frequently searched queries related to FM revealed consistent patterns across different countries, highlighting common concerns and misconceptions about the condition. These queries primarily focused on its potential connection to autoimmune diseases, diagnostic challenges, symptomatology, and treatment options. Table III presents a summary of these associated queries, ranked by their percentage increase in search volume, reflecting public interest and informational needs regarding fibromyalgia.

Discussion

This study provides a comprehensive analysis of online search behaviours related to FM across 16 countries, offering insights into public interest, temporal trends, and predictive modelling of search volumes. Our findings highlight significant variations in search interest in FM over a five-year period. Among the sixteen analysed countries, China, the UK, the USA and Canada exhibited the highest engagement, while Peru, Spain and Turkey recorded the lowest. South American and European nations demonstrated moderate to variable levels of search activity. The significant volume of online searches for FM in China is particularly intriguing, given its relatively low reported prevalence (0.03% to 0.12%) (30) compared to other countries, including neighbouring Asian nations such as Korea

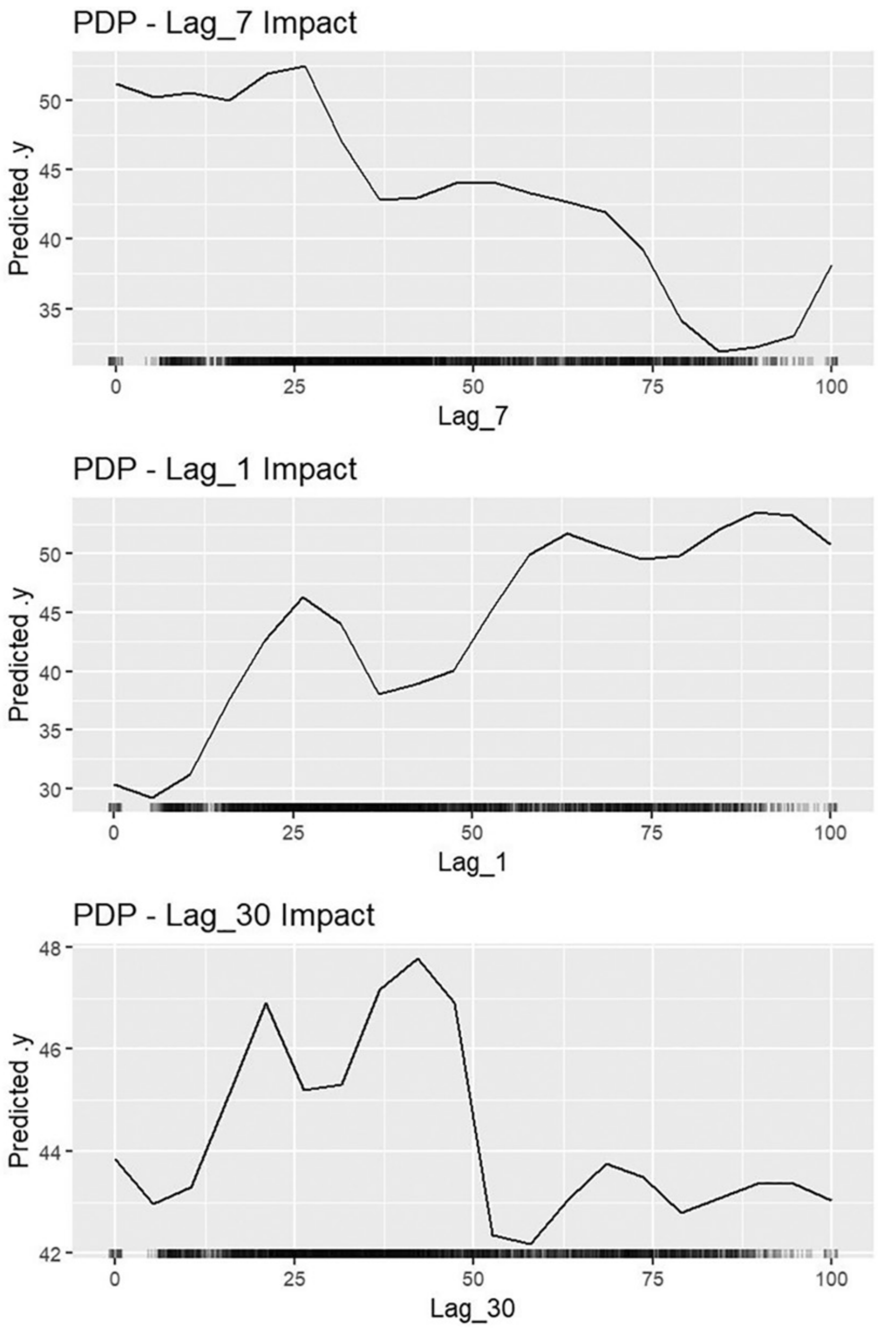

Fig. 8. Partial Dependence Plots (PDP) for lagged variables in search volume prediction. Effect of the three most influential lagged variables (Lag_1, Lag_7, and Lag_30) on the predicted search volume while keeping all other features constant.

(2.2%) (31) and Japan (2.1%) (32). This discrepancy suggests that, despite sharing similar demographic profiles and experiencing milder FM-related symptoms compared to other ethnic groups (33), Chinese patients may be underdiagnosed or may actively seek online information to better understand perceived symptoms of rheumatic diseases that can mimic FM (34).

The longitudinal analysis of Google Trends data revealed diverse patterns in search behaviour across different regions. Countries such as Brazil, Italy and the UK exhibited significant upward trends in FM-related searches, indicating increasing public interest and awareness. In contrast, Argentina, Canada, Greece and the USA demonstrated a steady decline in search volumes, possibly reflecting changing healthcare priorities, reduced media coverage, or improvements in clinical management reducing the need for online self-education. These findings may be attributed to the complexity of FM symptoms and the challenges Brazilian patients face in effectively communicating their condition to healthcare professionals (35). Furthermore, as highlighted by Duenas *et al*. (36), a major challenge faced by Brazilian patients is the limited access to diagnosis, treatment, and healthcare services. This is largely due to social disparities and the difficulty in reaching medical centres, often because of long distances. Italy exhibits some of the most significant regional health disparities in Europe, with self-reported poor health rates ranging from 4% in northern regions to 10% in the southern areas (37). FM severity appears to be highest among patients in Southern Italy, followed by those in the North, while individuals from Central Italy tend to experience a milder form of the condition (38). Consequently, the high online search volume in this country may be attributed to disparities that lead to considerable variations in access to healthcare services. Other countries, including China, France, Germany, Mexico and Spain, displayed stable search activity over the years, suggesting a consistent level of public interest without significant growth or decline. While a statistical correlation between search behaviour and disease prevalence cannot be reliably performed using time-series data, due to the limited availability of standardised longitudinal prevalence estimates for FM across different regions, an exploratory comparison using single-point prevalence data for each country reveals no clear or consistent association with mean search volumes. This finding is not unexpected, as FM prevalence is influenced by numerous factors, including age distribution, socioeconomic status, and whether the population resides in urban or rural settings (32, 39-41). Therefore, the integration of longitudinal, region-specific prevalence data, along with efforts to investigate changes in FM prevalence over time, would be essential to better contextualise digital search behaviours and assess their potential relationship with actual disease burden across populations.

Table III. Primary associated queries related to fibromyalgia ordered by their percentage increase in search volume.

Associated queries	Percentage increase
Fibromyalgia and COVID	900%
Fibromyalgia is an autoimmune disease	350%
Fibromyalgia symptoms in females	280%
Fibromyalgia diagnostic test	220%
Fibromyalgia novel treatments	190%
Duloxetine, pregabalin, gabapentin for fibromyalgia, side effects	110%
Fibromyalgia versus arthritis	100%
Is fibromyalgia a chronic illness	105%
What is fibromyalgia	95%
Fibromyalgia symptoms	90%
Hashimoto's disease fibromyalgia	85%

Seasonal decomposition analysis revealed country-specific fluctuations, with certain regions displaying predictable seasonal peaks. For example, Italy and Brazil showed mid-year search volume increases, while Turkey exhibited pronounced peaks in late autumn. In contrast, the USA displayed relatively stable seasonal trends with moderate fluctuations throughout the year. These findings suggest no clear seasonal variation in online searches related to FM. While an earlier study proposed a chronobiological theory indicating a seasonal pattern, where FM patients reported heightened pain, worsened mood, reduced energy, and poorer sleep quality between November and March, along with fewer symptoms from May to August, more recent studies have refuted this hypothesis. Instead, they demonstrate a lack of seasonal fluctuations in symptom reporting, indicating that symptom perception does not significantly vary by season (42). We can therefore infer that individuals searching for online information about FM are primarily patients themselves or individuals closely connected to them, such as family members or caregivers.

The ARIMA-based forecasting model projected stable FM search interest for most countries in 2025. However, Brazil, Canada and Mexico were expected to experience a continued rise in search volumes, while Germany and Venezuela were forecasted to exhibit slight declines. The UK emerged as the country with the most consistent and sustained search interest, reinforcing its role as a key region for FM-related online engagement. This finding is further supported by the fact that FM is one of the most prevalent causes of chronic pain in the UK, exerting a significant impact on both individuals and society. While the global prevalence is estimated to range between 2% and 6%, the prevalence in the UK remains a key area of study (43). Notably, China's search volumes were predicted to remain relatively high and stable, reflecting strong public attention to FM in the country.

Our machine learning analysis provided valuable insights into the key factors influencing online search behaviour related to FM. Feature importance analysis using SHAP values highlighted that short-term search history plays a crucial role in predicting future search trends. Specifically, Lag_1 (yesterday's search volume, SHAP: 2.81), Lag_7 (one-week prior search volume, SHAP: 2.77), and Lag_30 (one-month prior search volume, SHAP: 2.50) emerged as the most influential predictors. It is possible to argue that an increase in search volume over a relatively short period may result from public awareness campaigns, educational events, and patient association conferences, which can significantly influence online search activity by raising interest and engagement among both patients and the general population. However, the temporal effects of such initiatives appear to be short-lived, typically lasting from a few days to one month. This underscores the need for a structured and continuous approach to awareness efforts, with strategically planned educational campaigns throughout the year. By implementing periodic informational initiatives, it may be possible to sustain public interest, enhance patient knowledge, and promote the dissemination of scientifically validated information on FM. For instance, May 12th is recognised as the International Fibromyalgia Awareness Day by the American College of Rheumatology and the World Health Organization (44). Every year, individuals worldwide participate in fundraising events, charity runs, awareness campaigns and educational initiatives to highlight the impact of FM. However, despite this annual observance, no significant increase in online search activity was observed in May, except in Brazil. This suggests that such events may be insufficiently promoted or inadequately publicised, limiting their reach and public engagement. PDP analysis further illustrated the non-linear effects of temporal lags on predicted search volumes. Lag_1 showed a strong positive relationship with search interest, reinforcing the immediate impact of recent searches. However, Lag_7 displayed a saturation effect, where moderate past search volumes led to stable predictions, but higher past search activity resulted in declining future interest. This may reflect a behavioural pattern where an initial surge in searches leads to sufficient knowledge acquisition, reducing the need for continued inquiries. Our findings highlight the need for enhanced promotion of these events through both healthcare institutions and digital platforms to increase awareness, encourage participation, and improve the dissemination of information about FM.

The Internet can also play a role in enhancing well-being and alleviating pain and fatigue in FM patients. A recently published randomised controlled trial demonstrated that web-based positive affect interventions significantly improved symptom management and overall quality of life in individuals with FM (45). In fact, individuals with FM commonly rely on the Internet as their primary source of health information (46, 47). Moreover, a recent Knowledge, Attitude, and Practices (KAP) survey conducted among the Chinese FM population revealed that patients exhibited limited knowledge, a moderate attitude, and a lack of proactive management strategies regarding their condition (48). The study highlighted the need for targeted educational interventions as part of the treatment plan to improve patient awareness, self-management skills, and overall health outcomes. However, as previously highlighted, higher-quality websites often lack readability, making it challenging for patients to fully comprehend the content (49). It is therefore essential to promote the development

of scientifically accurate websites that are also easily understandable across different cultural backgrounds and literacy levels. Ensuring that online resources are both high in quality and accessible can enhance patient education, empower individuals with FM, and improve health literacy among diverse populations. Furthermore, artificial intelligence (AI) has the potential to enhance the development of personalized digital programs, offering customised insights, interactive educational content, and real-time guidance on FM-related topics (50).
Beyond search volumes, the analysis of associated queries provided insights into the most pressing concerns among individuals searching for FM-related information. The most frequently searched topics reflected a growing public interest in the relationship between FM and other health conditions, particularly COVID-19, autoimmune diseases, and arthritis. The search query “fibromyalgia and COVID” showed the highest increase (+900%), underscoring the impact of the pandemic on FM-related health concerns. Post-COVID syndrome has become increasingly recognised over time, with lingering symptoms persisting in many individuals following SARS-CoV-2 infection (51, 52). Notably, its clinical presentation shares similarities with FM, leading to the hypothesis that COVID-19 could act as a trigger for FM in predisposed individuals (1). In fact, at least 30% of FM patients report a preceding physical or psychological trigger before symptom onset (2). Several viral infections, including hepatitis C, HIV, parvovirus, and Epstein-Barr virus, have been linked to FM development (7), suggesting an abnormal host immune response to infection as a potential underlying mechanism (53). Given this evidence, it is plausible that SARS-CoV-2 and its post-viral sequelae may contribute to the onset of FM in susceptible individuals (54). Other top-ranking searches included “fibromyalgia is an autoimmune disease” (+350%), “fibromyalgia symptoms in females” (+280%), and “fibromyalgia diagnostic test” (+220%). These trends indicate ongoing uncertainties regarding the disease’s classification, gender disparities in symptom presentation, and the need for improved diagnostic approaches. Additionally, interest in pharmacological treatments, such as “duloxetine” and “pregabalin for fibromyalgia,” highlights the demand for information on medication efficacy and side effects.
The reliance on online health information presents both opportunities and challenges for public health. While digital resources provide a crucial platform for patient education, the variability in content reliability poses risks, especially for individuals with low health literacy. The increasing use of the Internet for health-related inquiries underscores the need for improved digital health education strategies, evidence-based online resources, and decision aids to guide patients toward credible sources of information.

Limitations

While this study provides valuable insights into online FM search behaviour, several limitations should be considered. First, Google Trends data are influenced by search engine algorithms and user behaviour, which may not fully reflect the actual prevalence of FM-related concerns. Another important limitation is that Google is not the primary search engine used worldwide. For instance, in China, Baidu (百度) is the most widely used platform for online searches. Additionally, internet accessibility is not uniform across all the analysed countries, and disparities in search volume may be influenced by differences in internet penetration, digital literacy, and the availability of web connectivity. Additionally, the analysis only captures relative search volumes rather than absolute numbers. Another limitation is the potential variability in language and cultural differences affecting search behaviour. While keywords were translated and validated by native speakers, nuances in medical terminology and public perception of FM may influence search patterns. In fact, despite careful translation and native validation, subtle differences in how fibromyalgia is referred to colloquially or medically across cultures may still influence search behaviours and introduce variability in relative search volumes. Future studies should explore qualitative aspects of search behaviour to gain deeper insights into user motivations and information-seeking strategies. Moreover, the study focused on Google Trends as the primary data source, but other platforms such as social media, health forums, and medical websites also play a crucial role in shaping public discourse on FM. Expanding the analysis to include these alternative sources could provide a more comprehensive understanding of online health-seeking behaviour.

Conclusion

This study highlights the significant role of online search behaviour in shaping public awareness and engagement with FM. The findings suggest that search interest varies across countries, with distinct temporal patterns and seasonal fluctuations. Predictive modelling confirmed the strong autoregressive nature of search trends, with recent search volumes being the most influential factor in forecasting future interest. The increasing volume of FM-related searches, particularly on topics related to COVID-19, autoimmune diseases, and pharmacological treatments, underscores the need for reliable digital health education resources. Healthcare providers and policymakers should leverage these insights to develop targeted online interventions, ensuring that patients have access to accurate, evidence-based information. Future research should continue to explore the intersection of digital health behaviour, disease awareness, and healthcare access to optimise patient education strategies in the evolving digital landscape.

Acknowledgments

We thank John Shaw and David Michael Abbott for their assistance with the English revision. We are also grateful to the Fondazione Paolo Procacci for the support in the publication process.

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