



Global Dynamics of Online-Learning Search Interest: An Advanced Multivariate Time-Series Analysis Across 20 Countries (2004–2021)

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ABSTRACT

This study examines the temporal evolution and cross-country interdependence of public search interest in “Online Learning” using a balanced monthly panel covering 20 countries from January 2004 to October 2021. The dataset contains 214 observations per country and 4,280 country month observations in total, with no missing values. The analysis combines univariate and multivariate time series procedures to characterize stationarity, autocorrelation, dynamic dependence, long run relationships, and the propagation of shocks. Augmented Dickey Fuller (ADF) and Kwiatkowski Phillips Schmidt Shin (KPSS) tests were applied to all series in levels and first differences. Eight series satisfied the combined stationarity criterion in levels, whereas 18 series satisfied it after first differencing. Autocorrelation and partial autocorrelation functions were examined up to 12 lags, followed by ARIMA and monthly seasonal SARIMA modeling for focal non-stationary series. For multivariate analysis, a parsimonious six country system comprising Argentina, India, Indonesia, Iran, Mexico, and the United States was selected to avoid excessive parameterization. Information-criterion selection supported a VAR(3) specification, while the Johansen procedure indicated a cointegration rank of five, motivating estimation of a VECM. Granger causality testing with false discovery rate adjustment identified 14 significant directional relationships. Impulse response functions show that most shocks are strongest at short horizons and generally attenuate over time, while forecast error variance decomposition reveals heterogeneous dependence on own and cross country innovations. Overall, the findings demonstrate that online learning search interest is both country specific and dynamically interconnected, with meaningful short run transmission and substantial long run linkage among the focal series.

Keywords: Online Learning, Search Interest, Time Series Analysis, Stationarity, Cointegration, Vector Autoregression (VAR), Granger Causality, Impulse Response Functions, Forecast Error Variance Decomposition, Cross Country Interdependence

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1. Introduction

Interest in online learning can be observed not only through formal participation statistics but also through information seeking behavior. Monthly search activity provides a longitudinal signal of when public attention to a topic rises, stabilizes, or experiences abrupt changes. The present dataset captures this signal for the query/topic “Online Learning” across 20 countries over nearly eighteen years. Because the data are observed repeatedly over time and simultaneously across multiple national contexts, they provide an appropriate basis for advanced time-series analysis.

The central analytical objective is twofold. First, the study characterizes the temporal properties of online-learning search interest within individual countries. Second, it investigates whether changes in search interest in one country contain predictive information about, or transmit dynamically to, search interest in other countries. This requires a sequence of complementary methods, including stationarity tests, auto correlation diagnostics, ARIMA/SARIMA models, vector autoregression, cointegration analysis, vector error correction, Granger causality, impulse response analysis, and forecast error variance decomposition.

The results are interpreted in the context of normalized search-interest indices. Values represent relative search popularity within each country’s series rather than directly comparable absolute counts of search queries. Accordingly, the analysis emphasizes temporal movement, persistence, predictability, and dynamic interaction rather than treating differences in index values as direct differences in absolute search volume.

2. Literature Review and Background

E-learning has long been heralded as a powerful avenue for increasing access to education and fostering social change [1]. When designed inclusively, online learning can be as effective as, or even more effective than, traditional in person instruction, depending on individual learner preferences [2, 3]. In recent years, the adoption of e-learning platforms has accelerated dramatically, driven by the Fourth Industrial Revolution, which has fundamentally reshaped the educational landscape through technologies such as artificial intelligence (AI), virtual reality, and data analytics [4, 5]. These platforms provide adaptive, scalable, and geographically unrestricted learning environments [6], offering the luxury of learning irrespective of temporal and spatial constraints.

The current era has also witnessed the integration of AI in various forms, including conversational chatbots and generative AI (GenAI) like ChatGPT, into teaching, learning, and scholarly activities. However, this integration is not without challenges, encompassing academic integrity, plagiarism, intellectual property violations, and other ethical and legal issues [7]. Among the prominent innovations in this domain are Massive Open Online Courses (MOOCs), which are online-based teaching programs designed to accommodate thousands of students without charging fees. MOOCs began appearing around 2009–2010, gained significant popularity, but have since experienced a decline [8]. Research indicates persistent scholarly interest in MOOCs, particularly in reducing dropout rates, though effective remedies remain elusive. Studies underscore the importance of fostering engagement and interaction, yet few have explored MOOCs in the context of business and management. Furthermore, as universities have sought to monetize these platforms, MOOCs have become less “massive” and less “open,” with key components like credit and certification now placed behind paywalls [8].

Central to the success of any online learning environment is the concept of student engagement. Defined broadly as the level of interest and effort a student demonstrates through weekly interaction with content and task completion (Partnership), engagement is consistently recognized as a key predictor of success in digital education. This study adopts a behaviorally grounded definition, consistent with prior research [9, 10, 11], emphasizing cognitive and behavioral engagement, as these dimensions are observable through platform

data. Furthermore, interaction-based engagement has been shown to positively influence learning outcomes [12]. Early theoretical models emphasize the interplay of affective, behavioral, and cognitive dimensions [13, 14]. More recently, engagement has become central to learning analytics, serving as a proxy for student attention, persistence, and potential risk of dropout [15]. In online settings, this has led to operationalizing engagement through digital traces such as login frequency, task completion, and interaction time, making it both measurable and actionable in real time.

To support engagement effectively, instructors must first be able to classify students based on their behavioral patterns and provide tailored interventions [16]. Real-time feedback in online education increasingly relies on the automated assessment of student engagement. Current research primarily evaluates engagement through the analysis of behavioral performance in classroom videos. Although existing methods consider temporal and multimodal cues, they predominantly rely on visual information and insufficiently model the cognitive rhythm of attention [17]. Complicating this task are several challenges, including defining engagement consistently, collecting fine grained behavioral data, selecting bias free analytical methods, and, significantly, addressing the impact of boredom. Engagement is intrinsically linked to the dynamic, unfolding process of learning itself, rather than being solely a reflection of a learner's initial intentions or static attributes [18, 19]. Moreover, it is a multifaceted psychological construct shaped by reciprocal factors that affect academic performance, comprising both affective (emotional and feeling based) and cognitive (intellectual and thought-based) dimensions, including elements such as interest, effort, and absorption [20-24].

3. Research Statement

This study investigates the temporal evolution and cross-country interdependence of public search interest in "Online Learning" using a balanced monthly panel of 20 countries spanning January 2004 to October 2021 (214 observations per country; 4,280 country-month observations). It combines univariate time series methods (stationarity testing, ACF/PACF diagnostics, ARIMA/SARIMA modelling) with multivariate dynamic analysis (VAR lag selection, Johansen cointegration, VECM, Granger causality with FDR adjustment, impulse response functions, and forecast error variance decomposition) to characterise within country dynamics and the short run transmission and long run linkage of search interest shocks across a focal six country system (Argentina, India, Indonesia, Iran, Mexico, and the United States)

3.1 Research Gap

Existing literature on e-learning, MOOCs, student engagement, and AI-enhanced online education largely focuses on pedagogical effectiveness, platform design, learner behaviour within specific systems, or single-country descriptive trends. There is a notable absence of rigorous, multi-country multivariate time series analysis that:

- Examines long run cointegrating relationships and short run predictive (Granger) linkages in normalised search interest series across diverse national contexts;
- Quantifies the propagation of shocks (impulse responses) and the relative contribution of domestic versus foreign innovations to forecast uncertainty (FEVD);
- Integrates stationarity diagnostics, univariate modelling, and system wide dynamic modelling on a balanced, nearly two decade panel covering both high and low mean interest countries.

Consequently, the global interconnectedness of public attention to online learning remains under explored from a formal time series perspective.

3.2 Research Issues / Purpose

3.2.1 Primary purpose

To determine whether, and how, public search interest in online learning evolves over time within individual countries and transmits dynamically across countries.

3.2.2 Specific research issues / objectives

1. Characterise the temporal properties (stationarity, autocorrelation structure, and univariate dynamics) of online learning search interest series for 20 countries.
2. Identify the appropriate lag structure and long run equilibrium relationships among a parsimonious six-country subsystem.
3. Detect statistically significant directional predictive relationships (Granger causality) after multiple testing correction.
4. Map the short run propagation of shocks (impulse response functions) and the sources of forecast uncertainty (forecast error variance decomposition) within the multivariate system.
5. Interpret the combined evidence to show that online learning search interest is simultaneously country-specific and dynamically interconnected.

3.3 Research Design

Quantitative, longitudinal, multivariate time series research design employing a balanced panel of secondary search interest data.

3.3.1 Data

Source: Monthly Google Trends style normalised search interest indices for the topic/query “Online Learning”.

Coverage: 20 countries, January 2004 – October 2021 (214 time points each; no missing values).

Nature of the measure: Relative popularity within each country’s own series (peak = 100); not absolute search volume.

3.4 Analytical framework

1. Univariate stage

Stationarity assessment (ADF + KPSS) on levels and first differences.

ACF/PACF diagnostics (lags 1–12).

ARIMA and seasonal SARIMA modelling of focal non-stationary series.

2. Multivariate stage (restricted to six countries to avoid over parameterisation)

Information criterion lag selection → VAR(3).

Johansen cointegration test → rank 5 → VECM estimation.

Granger causality testing with false discovery rate adjustment.

Impulse response functions (12 period horizon).

Forecast error variance decomposition.

3.5 Justification for design choices

- Balanced panel and absence of missing data support lag based multivariate procedures.
- Restriction to six countries maintains a feasible parameter to observation ratio.
- Combination of stationarity, cointegration, and structural tools (IRF, FEVD) allows simultaneous examination of short run transmission and long run linkage while remaining faithful to the normalised nature of the data.

This design yields an integrated empirical characterisation of both the local trajectories and the global dynamic interdependence of online learning search interest.

4. Data and Study Design

4.1 Dataset scope

The dataset consists of monthly observations from January 2004 through October 2021, yielding 214 time points for each of 20 countries. The coverage spans the Americas, Europe, Asia, and Africa. The complete panel therefore contains 4,280 country month observations. The dataset is balanced and contains no missing or null values, which is important for multivariate lag based procedures because these methods require aligned observations across all included series.

The monthly date is the temporal identifier, while each country is represented by a normalized search interest series. Values range from negligible or baseline interest to a historical peak index of 100 within the relevant country's series. This scaling supports analysis of within series temporal dynamics and relative movement, while direct comparisons of absolute search volume between countries should be made cautiously.

4.2 Descriptive distribution of search interest

The descriptive statistics reveal substantial heterogeneity in both average search interest and temporal variability. The United States has the highest mean value (49.99), followed by Germany (40.72), the United Kingdom (40.48), and India (29.07). These countries also exhibit comparatively high median levels, indicating sustained interest over substantial portions of the observation period. By contrast, Argentina (3.57), Peru (3.65), Indonesia (4.91), Ukraine (5.05), Turkey (5.84), Colombia (6.38), Iran (6.89), and Russia (3.31) have much lower average levels.

Variability is also uneven across countries. India has a standard deviation of 17.16, Spain 16.91, Germany 16.17, Poland 16.15, the United States 15.72, and South Africa 15.47. The Philippines displays pronounced dispersion relative to its mean, with a standard deviation of 19.34 against a mean of 12.78, indicating episodic changes around a relatively low central level. In contrast, the United Kingdom combines a high mean with a more moderate standard deviation of 12.10 and a minimum of 21, indicating a sustained baseline.

The minimum and median values reinforce the distinction between sustained and episodic engagement. The United States and United Kingdom retain minimum values of 22 and 21, respectively, while India retains a minimum of 9. Several other countries reach zero at some point during the sample. Every series reaches a maximum of 100 because the measure is normalized to the peak historical value within the corresponding series; a shared maximum therefore does not imply identical absolute search volume.

5. Analytical Framework

5.1 Stationarity assessment

Stationarity is a foundational requirement for many time-series models because persistent trends or changing moments can generate misleading relationships. The ADF test evaluates the null hypothesis that a unit root is present, whereas the KPSS test evaluates the null hypothesis of stationarity. Considering both tests together provides a more balanced basis for classification than relying on a single procedure.

The tests were applied to all 20 series in levels and after first differencing. Eight series satisfied the combined ADF/KPSS stationarity criterion in levels, whereas 18 series satisfied the criterion after first differencing. The large improvement after differencing indicates that non-stationarity in many country series was primarily associated with persistent level movement rather than an absence of short run structure. The remaining cases require cautious interpretation and underscore that stationarity properties are heterogeneous across countries.

5.2 ACF and PACF diagnostics

Autocorrelation and partial autocorrelation functions were computed for the differenced series through 12 lags, corresponding to one year of monthly lags. The figure shows that correlations vary across countries and across lags, but the differenced series generally fluctuate around the zero line rather than displaying a common

pattern of long, persistent auto correlation. Several series exhibit isolated positive or negative spikes, indicating short horizon dependence that differs by national context.

Country	N	Mean	SD	Min	Median	IQR	Max
United States of America	214	49.99	15.72	22.0	51.5	24.0	100.0
Germany	214	40.72	16.17	0	38	20.75	100
United Kingdom	214	40.48	12.1	21	38	12	100
India	214	29.07	17.16	9	24	20.75	100
Spain	214	25.95	16.91	0	23	19	100
Italy	214	17.17	13.61	0	15.5	12	100
South Africa	214	15.86	15.47	0	12	11	100
Poland	214	15.79	16.15	0	12	12	100
Philippines	214	12.78	19.34	0	6	6	100
Mexico	214	10.91	13.3	0	7	15	100
France	214	10.2	10.38	0	9	7.75	100
Brazil	214	8.21	10.5	0	7	7.5	100
Iran	214	6.89	11.38	0	3	7	100
Colombia	214	6.38	10.81	0	3	9	100
Turkey	214	5.84	11.54	0	3	3	100
Ukraine	214	5.05	10.22	0	2.5	7	100
Indonesia	214	4.91	10.25	0	2	4	100
Peru	214	3.65	8.26	0	0	5	100
Argentina	214	3.57	8.44	0	2	4	100
Russia	214	3.31	11.98	0	1	1	100

Table 1. Descriptive statistics of country-level online-learning search interest

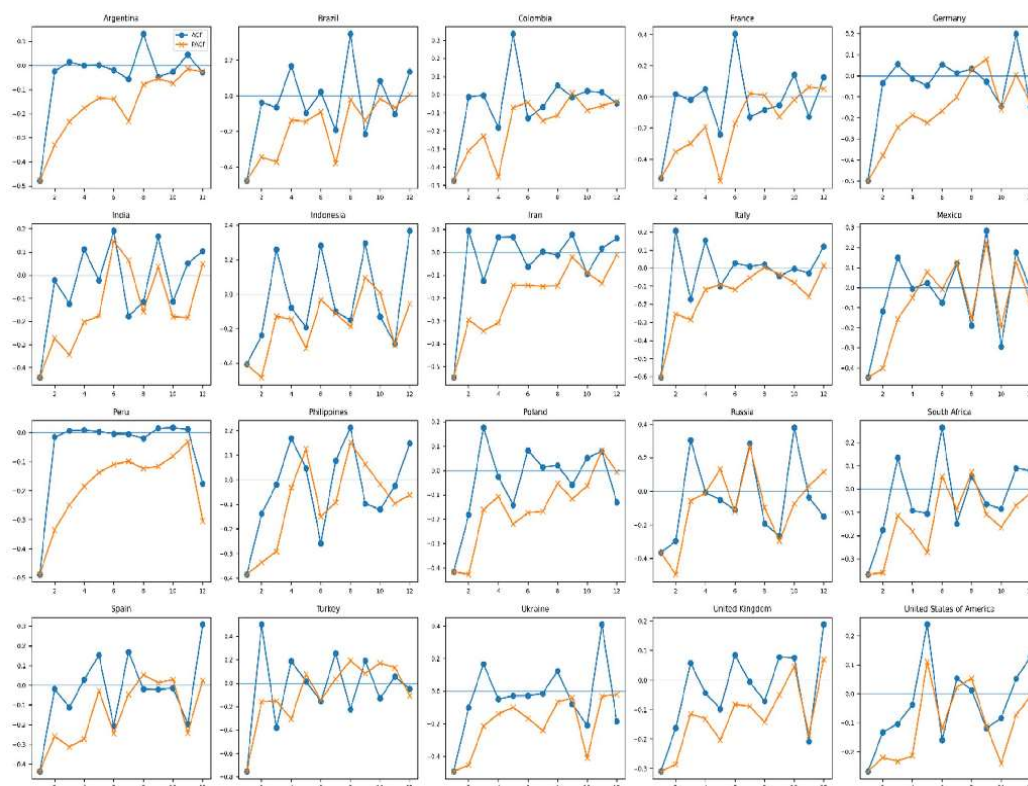


Figure 1. ACF and PACF diagnostics for the differenced country level online learning search interest series (lags 1–12). Blue denotes the ACF and orange denotes the PACF

5.3 ARIMA and SARIMA modeling

ARIMA models were estimated for focal non stationary series to represent short run autoregressive and moving-average dynamics after the required differencing. Because the observations are monthly, SARIMA models were also estimated with a monthly seasonal structure to assess whether recurring within year dependence could improve the representation of the data. The supplied output does not report one universal preferred ARIMA or SARIMA order for all 20 countries; interpretation should therefore remain series specific rather than assuming that one common univariate model describes every national trajectory.

6. Multivariate Dynamic Analysis

6.1 Focal multivariate system

The multivariate analysis focused on Argentina, India, Indonesia, Iran, Mexico, and the United States. This parsimonious selection was necessary because estimating an unrestricted VAR/VECM for all 20 series with only 214 monthly observations would require a large number of lagged parameters relative to the available sample size. Restricting the system reduces overparameterization and makes the estimated dynamic relationships more interpretable.

6.2 VAR lag selection and cointegration

Information criterion selection supported a lag order of three, resulting in a VAR(3) structure for the focal system. Current movements in each series were therefore modeled using information from the preceding three monthly observations of all six variables. A three lag specification captures short run propagation while remaining parsimonious relative to the sample length.

Johansen cointegration testing indicated a cointegration rank of five among the six focal series. This provides evidence of substantial long run dependence: although individual series may be non stationary in levels, their

movements are not independent over the long run. Because cointegration was established, a VECM was estimated to represent both short run changes and long run equilibrium relationships. The VECM framework is therefore preferable to interpreting a differenced VAR alone when long run linkage is part of the analytical objective.

6.3 Granger-causality results

Granger-causality tests were conducted at lag 3 and adjusted for multiple testing using a false-discovery-rate procedure. Fourteen directional relationships remained statistically significant at the 5% level after correction. Here, Granger causality indicates incremental predictive content: past values of one country's series improve prediction of another country's current series after accounting for the multivariate lag structure. It should not be interpreted as proof of direct real world causation.

The strongest reported relationships include Argentina → Indonesia, Iran → Argentina, Indonesia → India, and India → Iran, all with FDR adjusted p-values below 0.001. Additional significant pathways include India → Argentina (0.0017), Mexico → Indonesia (0.0017), Iran → Mexico (0.0037), and United States → India (0.0065). Together, these results indicate that the focal countries form a connected predictive system rather than six isolated time series.

Cause	Effect	FDR-adjusted p-value
Argentina	Indonesia	<0.001
Iran	Argentina	<0.001
Indonesia	India	<0.001
India	Iran	<0.001
India	Argentina	0.0017
Mexico	Indonesia	0.0017
United States	India	0.0065
Iran	Mexico	0.0037

Table 2. Selected significant Granger-causality relationships

5.4 Impulse-response analysis

Impulse-response functions were generated over a 12-period horizon to examine how a shock to one series propagates through the focal multivariate system. Each panel represents the estimated response of a target country to an innovation in a source country, with dashed bounds indicating uncertainty around the estimated response.

A dominant visual feature is the concentration of the largest movements at short horizons. Own-series responses are generally strongest immediately after a shock and then decline toward zero. Cross-country responses are more heterogeneous: some shocks produce temporary positive or negative reactions, while many responses oscillate around zero and diminish as the forecast horizon increases. This pattern indicates short-run transmission mechanisms but suggests that many individual shocks do not produce permanently expanding responses over the one year horizon.

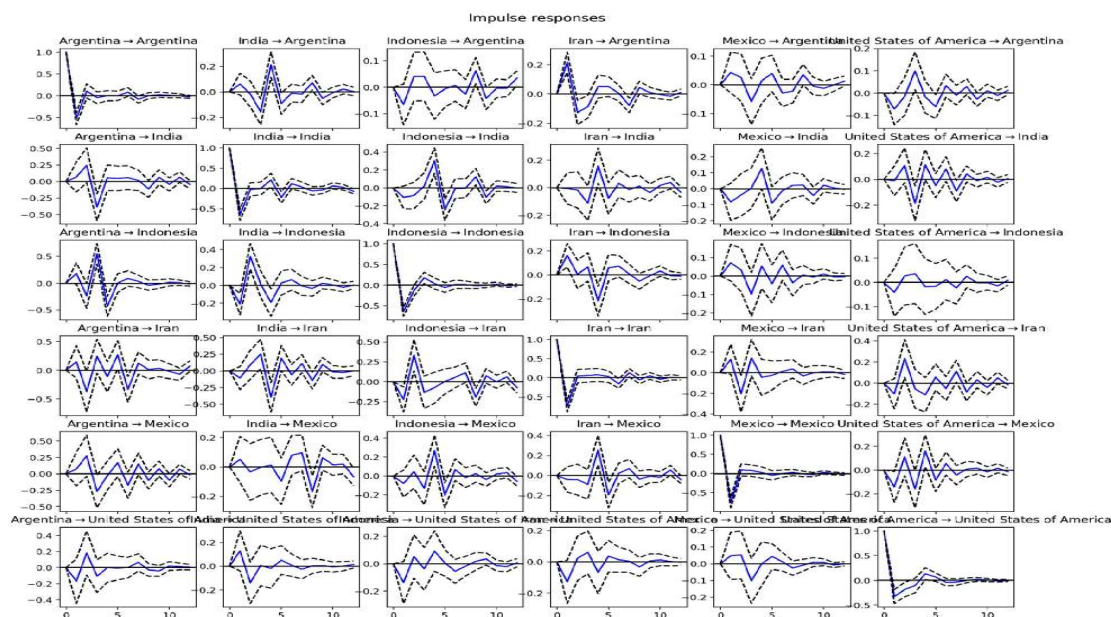


Figure 2. Twelve period impulse response functions for the six-country focal system. Panels show the response of the country named after the arrow to a shock in the country named before the arrow, dashed lines represent uncertainty bounds

6.5 Forecast error variance decomposition

Forecast error variance decomposition (FEVD) was used to determine the proportion of forecast uncertainty in each focal series attributable to innovations originating from itself and from the other countries. The heat map summarizes these contributions as percentages.

The diagonal cells show that own innovations account for a substantial share of forecast uncertainty for all six countries, with especially strong own contributions visually apparent for India, Mexico, and the United States. The off diagonal cells are not uniformly negligible. Argentina shows a visible contribution from Indonesia, Indonesia receives a noticeable contribution from Argentina, and Iran shows a comparatively prominent contribution from India. These cross country shares complement the impulse response and Granger causality evidence by demonstrating that forecast uncertainty is not determined exclusively by each country's own shocks.

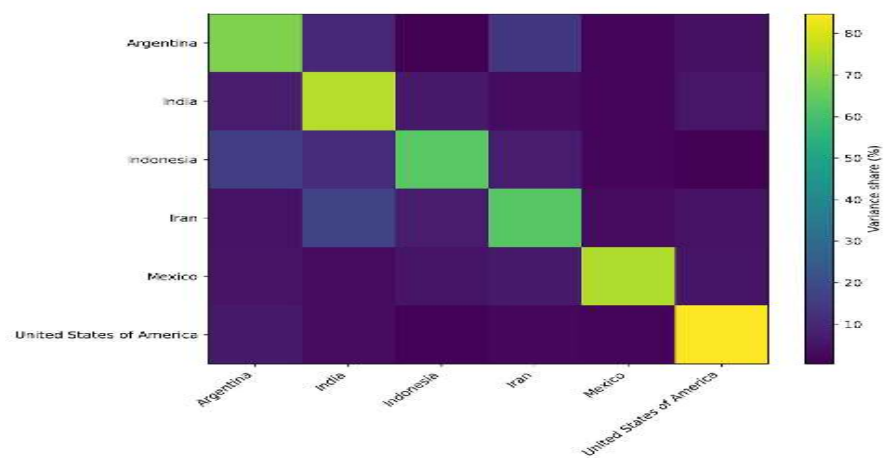


Figure 3. Forecast error variance decomposition for the six-country focal system. Cell intensity represents the percentage contribution of innovations in the column country to forecast uncertainty in the row country

7. Discussion

The combined evidence points to three broad characteristics of global online-learning search interest. First, the level and variability of interest differ substantially across countries. High-mean countries such as the United States, Germany, the United Kingdom, and India exhibit sustained or comparatively elevated interest over the sample, whereas several lower mean countries show much smaller baseline values. Second, many series require differencing to satisfy standard stationarity criteria, indicating that analyses based directly on levels should account for persistence and long run movement. Third, the focal multivariate system exhibits both long run linkage and short run directional dependence.

The cointegration rank of five is particularly important because it implies extensive long run restrictions among the six focal series. This provides a statistical basis for using a VECM and for interpreting short run shocks in the context of a system with equilibrium relationships. At the same time, the impulse response plots indicate that many short run disturbances attenuate rather than producing indefinitely expanding responses. The combination of cointegration and transitory short run responses is consistent with a system in which deviations can occur but remain embedded within broader long run relationships.

The Granger causality network further shows that predictive relationships are directional. Indonesia contributes predictive information for India, while India contributes predictive information for Iran and Argentina. Iran contributes predictive information for Argentina and Mexico, and the United States contributes predictive information for India. These findings should be interpreted as temporal information flows in the observed search interest indices rather than as evidence of direct social, institutional, or policy transmission. The available data do not identify the underlying mechanisms.

The FEVD analysis adds a forecasting perspective. Strong diagonal contributions show that each country's own historical innovations remain central to future uncertainty. However, visible off diagonal contributions demonstrate that the multivariate system contains non redundant information. For selected relationships, shocks originating elsewhere explain a meaningful portion of forecast uncertainty, suggesting that multivariate forecasting may be particularly useful when the objective is to capture connected episodes of changing public attention.

8. Practical and Methodological Implications

The findings suggest that stationarity testing should precede regression or multivariate modeling because the level series are heterogeneous and many become stationary only after differencing. The choice between VAR and VECM should be guided by cointegration evidence; when long-run relationships are established, differencing away all level information can obscure important equilibrium structure. Granger causality results should also be reported with multiple testing control when many directional tests are performed, as was done here using false discovery rate adjustment.

For forecasting applications, future work can compare out of sample performance across univariate ARIMA/SARIMA and multivariate VAR/VECM specifications. The supplied analysis establishes the structural and dynamic relationships needed for such a comparison, but it does not provide a complete out of sample forecast-accuracy table. A subsequent study could use rolling-origin evaluation with metrics such as RMSE, MAE, MAPE, or other scale appropriate measures.

9. Limitations

Several limitations follow directly from the data and reported analysis. First, the normalized index measures relative search interest rather than absolute search volume, limiting direct cross country comparisons of the

magnitude of public demand. Second, Granger causality measures predictive precedence and incremental forecasting information, not structural causation. Third, the multivariate system was intentionally restricted to six countries to maintain a feasible parameter to observation ratio; therefore, the VAR/VECM results should not be interpreted as a complete model of all 20 countries simultaneously.

The supplied results establish cointegration and dynamic dependence but do not identify the external events or mechanisms responsible for those relationships. The observed linkages may reflect common global shocks or synchronized changes in educational and technological behavior, but the present data do not isolate those mechanisms. In addition, one attached figure concerns URL recovery and web accessibility rather than the online learning time series dataset; it was not incorporated into the empirical interpretation because it does not visualize the study variables.

10. Conclusion

This study provides an integrated view of global online-learning search interest through descriptive, univariate, and multivariate time series analysis. The 20-country dataset exhibits marked cross national differences in average interest, dispersion, and baseline behavior. Stationarity testing shows that first differencing substantially improves the suitability of most series for conventional dynamic modeling, while ACF/PACF diagnostics reveal heterogeneous short run dependence.

Within the focal six country system, VAR lag selection supports a three month dynamic structure, and the Johansen result establishes strong cointegration with rank five. The resulting VECM captures both short run adjustment and long run dependence. Granger causality testing identifies 14 statistically significant directional relationships after false discovery rate correction, confirming that selected national series contain useful predictive information for one another.

The impulse response and FEVD results provide complementary evidence that shocks propagate through the system in heterogeneous ways. Most responses are strongest at short horizons and generally decay, while forecast uncertainty remains strongly influenced by own innovations but also reflects selected cross country contributions. Taken together, the findings show that online learning search interest is simultaneously local and interconnected: national trajectories retain distinctive characteristics, yet changes in one part of the system can contain information about future developments elsewhere.

Data and Analysis Statement

All interpretations in this expanded paper are based on the descriptive statistics, time series results, Granger-causality table, and relevant figures supplied in the attached analysis document. No external data or unsupported causal mechanisms were introduced.

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