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IQ-UFG WEBSCIENCE: THE ARROW OF TIME AND PUBLIC ENGAGEMENT IN THE CONTEXT OF THE TRANSPANDEMIC

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ABSTRACT
The meaning of time has been a recurring theme in popular science articles in different media, although they do not consider the temporal progressivity, represented by the "arrow of time", nor the influence of multiple temporal scales on the power and mechanisms of public engagement. In this article, the performance indicators of the webinars of the WebCiência IQ-UFG channel on YouTube® were analyzed over multiple time scales, using asymmetric eigenvector (AEM) maps. The results allowed us to incorporate the unidirectionality of the time vector between the webinars, preserving the temporal structure of causality. The temporal trend (large scale) represented the transition from remote and face-to-face teaching in the transpandemic, while the strategy and resources made available by the management team were important in engaging the public, with emphasis on the selected themes (intermediate scale). The AEM modeled both the multiscale temporal influence and the increasing variance in time of views, likes, and comments of webinars, contributing to the evaluation of the temporal effects associated with social media engagement.

Keywords: Scientific dissemination. Social media. YouTube®. Chemistry. Temporal trend.

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INTRODUCTION

The notion of time is central to studies in which temporal variables influence behaviors and patterns (Hammond, 2013). The way people perceive and experience time flowing in one direction, that is, the perception of the progressiveness of time, is represented by a linear and unidirectional arrow (Kasmire; Zhao, 2021). The "arrow of time" is, therefore, a basic concept in physical processes, such as in the description of movements and in the transfer and transformation of energy and increase of entropy in spontaneous processes (Leite; Andrade-Neto, 2013), as well as in biochemical processes, such as in the regulation of different biological processes and in evolution through natural selection (Verniest; Greulich, 2019). In the social sciences, time cannot be ignored in the analysis of historical changes (Moura Filho, 2008), economic trends and cultural evolutions (Whitrow, 2005), such as language, which "[...] it requires a sequential temporality for the ordering of the conversation. Without time, there are only fragmented mirages of communicative relations [...]" (Marzochi, 2017, p. 13). The influence of time and its directionality permeates all levels of knowledge organization, which reinforces the need for a rigorous understanding of its properties and impacts (Lana *et al.*, 2018).

In this context, analyses aimed at capturing temporal variability are essential to identify patterns and behaviors in various natural phenomena (Legendre; Gauthier, 2014). The study of temporal variability, by means of statistical techniques, enables the modeling of uncertainties and the quantification of fluctuations that occur over time (Souza; Carmo; Welch, 2023). These analyses not only help describe the behavior of time-dependent phenomena, but also allow predictions and inferences about future trends. The understanding of temporal variability and its adequate modeling have significant practical implications, allowing decision-making ranging from public policies to the optimization of industrial and technological processes (Pietrobon-Costa; Fornari Junior; Santos, 2012; Souza; Carmo; Welch, 2023).

Statistics applied to the analysis of time series and spatiotemporal data has evolved substantially, allowing the investigation of the influence of time on variables of interest (Legendre; Gauthier, 2014). Among the analysis techniques, Moran*'s Eigenvector Maps (MEM) and* Asymmetric Eigenvector Maps *(AEM) stand out*, used to model spatial and temporal variability and dependence (Blanchet; Legendre; Borcard, 2008; Sharma *et al.*, 2011). These techniques offer an efficient approach to capture patterns of spatial and

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temporal correlation or even causation (Baho *et al.*, 2015), which are not detected by traditional methods.

MEM have been successfully employed to extract symmetric dependencies, in which the previous and subsequent states have equal influence on the current state, and are widely applied in the modeling of ecological processes (Brind'amour *et al.*, 2018) and biological (Benito *et al.*, 2019) and in geosciences (Vandam; Kaptijn; Vanschoenwinkel, 2013). SEA, in turn, are particularly useful in studies in which there are directional flows of information, energy, or matter, such as in rivers (Parreira; Tessarolo; Nabout, 2023; Tripodi *et al.*, 2023), winds (Horváth; Vad; Ptacnik, 2016), ocean currents (Svensson; Norberg; Snoeijs, 2014), genetic structure as a result of geographic isolation (Dalongeville *et al.*, 2018) or biological dispersal (Castillo-Escrivà *et al.*, 2016), in addition to the directional trend of time (Angeler *et al.*, 2015; Baho *et al.*, 2015; Blanchet; Legendre; Borcard, 2008; Goyer *et al.*, 2014; Lévesque *et al.*, 2017), in which asymmetric dependency must be retained, modeled, interpreted and predicted.

The application of these techniques in temporal variability analyses allows a better understanding of the underlying processes and helps in the identification of hidden patterns of temporal dependence, especially if the samples occur without replication at the level of the sampling units in time (Behpour *et al.*, 2021). Such a condition prevents the formulation of hypotheses in classical methods, due to the lack of replicated observations (Legendre; Gauthier, 2014).

The Covid-19 transpandemic[6] , declared by the World Health Organization (WHO) in March 2020, has had significant impacts on several sectors, including education (Sá *et al.*, 2020). Due to the need for social distancing measures and the rapid spread of the virus, educational institutions were forced to interrupt their face-to-face activities. As an alternative to the restrictions imposed, the Institute of Chemistry of the Federal University of Goiás (IQ-UFG) transposed the program of face-to-face seminars "Chemistry at 13" to the form of webinars within the scope of the WebCiência IQ-UFG extension action on the YouTube platform®, during the emergency remote teaching period (ERE). The program preserved this format even after the resumption of teaching activities, promoting the exchange of

[6] The term transpandemic, proposed at the Brazilian Center for Health Studies (CEBES DEBATE, 2021), refers to the period beyond the peak of the Covid-19 pandemic, which began on March 11, 2020, and covers the time after May 5, 2023, considered the end of the Public Health Emergency of International Concern related to Covid-19 by the World Health Organization. Its conception incorporates a dynamic whose effects are still felt today and reflects the imbalances that contribute to various forms of illness and that cause repercussions that have not yet been fully dimensioned in all areas of society.

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ideas and collaboration between different disciplines. In addition, it enabled the participation and dissemination of knowledge in research activities, both at IQ-UFG and in other teaching and research institutions, as well as in public administration bodies and entities and initiatives linked to the industrial sector.

The migration to the social platform and the maintenance of virtualization contributed to the analysis of the channel's performance indicators, resulting in information on the dynamics of the extension action (Sgobbi *et al.*, 2023) that included participant engagement along the time scale of posting videos during the transpandemic, extracted and modeled through MEM (Barbosa *et al.*, 2025). To complement this information, it becomes important to evaluate the situation in which a directional and asymmetric process, represented by the "time arrow", influences the performance variables of the channel, which can be achieved through AEM autofunctions on multiple time scales.

METHODOLOGY

This research is applied in nature and uses qualitative and quantitative indicators from eighty webinars of the WebCiência IQ-UFG channel, collected from August 3, 2020 to August 21, 2023. The symmetric temporal influence (MEM) of these webinars was described in a previous study by the authors (Barbosa *et al.*, 2025). Briefly, the channel's performance metrics (views, likes, and comments) were arranged in the columns of a response matrix (80 × 3), whose rows represented the chronological order of the webinars, while an explanatory matrix (80 × 10) contained quantitative variables (post-live views and total audience, internal and external to UFG) and qualitative variables representing the type of teaching (remote or face-to-face), management team (two levels), year (four levels), cycle or academic semester (two levels), theme (ten levels) and similarity class (three levels) of the webinars.

The temporal variables (AEM) were derived from a matrix of time (nodes) and directional connections (edges), of equal weight, representing the intervals between the days of posting the webinars in relation to the date of channel creation (July 15, 2020). The factorization of the time×connection matrix, by the decomposition of singular values (SVD), led to the AEM orthogonal eigenvectors (Figure 1).

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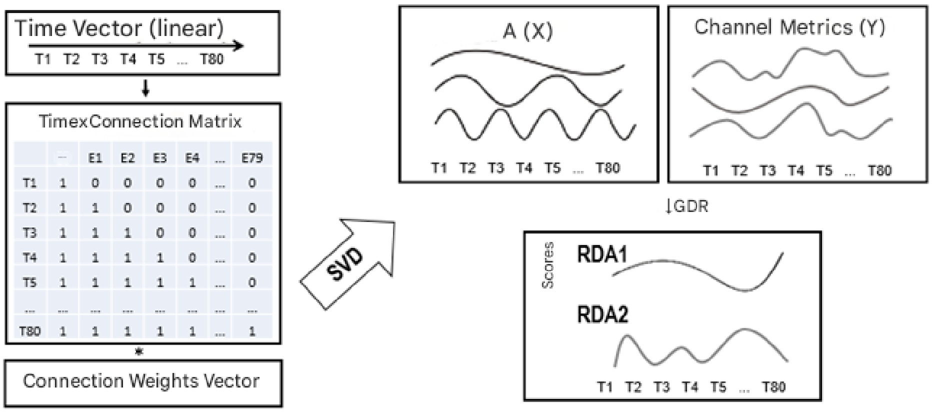
Figure 1 – Schematic representation of the data vectorization process in the analyses described in this study. The time vector is converted to AEM explanatory variables (X) by the singular value decomposition (SVD) method of the time×connections matrix. Redundancy analysis (RDA) identifies webinars with similar trends from channel performance metrics (Y), which represent temporal patterns at different scales.



Source: Prepared by the authors (2025).

After obtaining the AEM, the selection of the significant subset was carried out by means of redundancy analysis (RDA) with double criteria, which involved the maximization of the square of the coefficient of determination, adjusted by the degrees of freedom (R2aj), and the control of the type I error by the Sidák correction (Bauman *et al.*, 2018). The six significant BSAs were incorporated into the explanatory matrix (80 × 16), which was submitted to the selection of predictor variables by means of consecutive RDAs. The best model was based on the variance inflation factor (VIF), assuming the absence of multicollinearity for VIF < 5, and on the values of R2aj and probability (*p*), using Monte Carlo permutations (999 permutations). The selected variables were grouped into explanatory subsets and the pure and overlapping fractions of explained variance were quantified by partitioning the total explained variation (Peres-Neto *et al.*, 2006) with partial RDA (pRDA).

In the pRDA, four predictor subsets were considered: (1) channel indicators, with post-live views and total participant counts, in addition to classes 2 and 3 of similarity between webinars (Barbosa *et al.*, 2025); (2) the large time scale, represented by AEM1, AEM3 and AEM5; (3) the intermediate scale, consisting of the SEM6, SEA7, AEM17 and (4) the fine temporal scale, consisting of the AEM21, AEM40 and AEM42. In this technique, the fractions of explained variation were represented by means of Venn diagrams of the R2aj values. To interpret the temporal structure, linear regressions of the adjusted scores of the significant canonical axes of the RDA on the explanatory matrix were used. The regression coefficients were previously validated for the normality of the regression residuals with the Shapiro-Wilk test.

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In addition to these techniques, the multiple comparisons of multiscalar temporal variance were adjusted by Holm's correction, and the envelopes describing the confidence intervals (95%) in the multivariate variograms were used to evaluate the independence of the temporal scales around the mean variance, $\gamma(h)$ (Wagner, 2004), allowing to estimate the magnitude of the spatial dependence between the webinars (Barbosa *et al.*, 2025). The number of lags (h = 14) was determined by Sturges' rule (Scott, 2009), avoiding the arbitrary inflation of the temporal variation as a function of the distances (days) between posts.

Before the analyses, the response matrix was transformed by ln(y+1). To detect monotonic trends in the matrices, the non-parametric Mann-Kendall test was applied (Moreira; Naghettini, 2016). Values of $p < 0.05$ were considered significant and the analyses were performed in the R program (R Core Team, 2022).

RESULTS AND DISCUSSION

The understanding of time and its influence on natural and social processes constitutes one of the basic axes of scientific knowledge. The notion of time permeates several areas of science, from physics to social sciences, in the study of historical transformations and population dynamics. Time has been treated not only as a continuous and homogeneous dimension, but as a factor that can vary at different scales, influencing the dynamics and variability of the observed phenomena, even if the temporal representation is subtle or implicit in the data.

Most data is (implicitly) ordered or time-dependent, potentially allowing a hidden "time arrow" to affect the performance and results of statistical analysis methods (Kasmire; Zhao, 2021). In view of this, the modeling and analysis of temporal variability have become essential for a more accurate understanding of complex processes and the challenge lies, in particular, when the unidirectionality (irreversibility) of time needs to be preserved, that is, when the previous states can influence the later ones, but not vice versa, because in this way, the temporal structure of causality is explicitly preserved (Baho *et al.*, 2015; Blanchet; Legendre; Borcard, 2008).

In this study, the unidirectional influence of time on the performance indicators of eighty webinars of the WebCiência IQ-UFG channel and on the identification of factors in their trajectory throughout the Covid-19 transpandemic were evaluated. To preserve the linear and directional structure of time, asymmetric eifunctions were used through AEM

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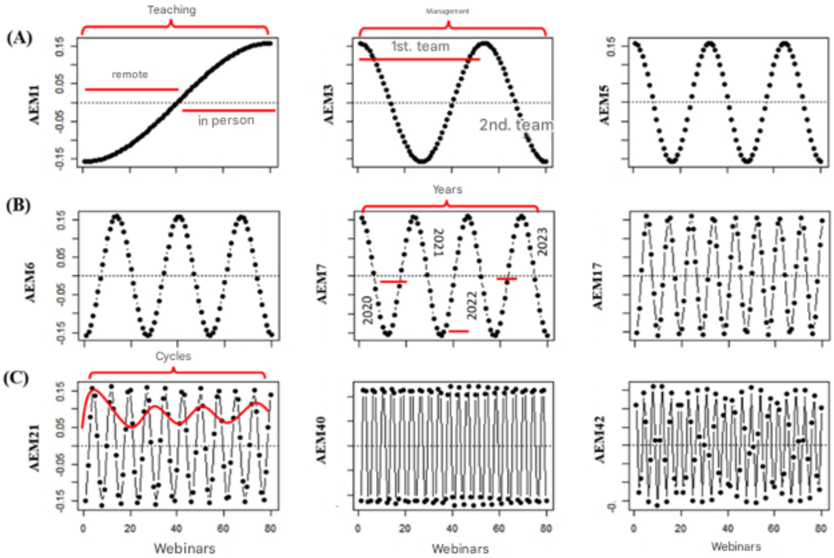
(Sharma *et al.*, 2011). Of the 79 WEAs generated by the linear vector of time, six (Figure 2) were selected by the RDA (data not shown).

Figure 2 – Asymmetric eigenvector (AEM) maps describing the multiscales of time: (A) large; (B) intermediate; (C) thin.



Source: Prepared by the authors (2025).

Significant BSAs were reorganized along the large (AEM1, AEM3, AEM5), intermediate (AEM6, AEM7, AEM17) and fine (AEM21, AEM40, AEM42) temporal scales. The first eigenvector (AEM1) accounted for significant monotonic trends in the response variables, represented by the performance metrics of the webinars, using the Mann-Kendall test ($-4.930 > z > -2.317$; $p < 0.021$). The negative values indicate that performance metrics decreased with the advance of posting time, with an inflection point in the 38th webinar, coinciding with the (partial) resumption of face-to-face activities at UFG in January 2022 (2021/2 cycle). This result reinforces how much the transpandemic disrupted educational systems, demanding emergency remote teaching that coincided with the increase in the use of social networks (Greenhow; Lewin; Willet, 2023).

Subsequent eigenvectors have sine wave properties and are suitable for modeling temporal changes from slow to progressively shorter fluctuating frequencies (Blanchet; Legendre; Borcard, 2008, Legendre; Gauthier, 2014; Sharma *et al.*, 2011), to those associated with the dynamics of local and online extension action, represented by the thin temporal scale (Borcard *et al.*, 2004). EARL3 seems to be related to the management teams of the extension action, while ONEM7 and ONE21 may be associated with the academic years and cycles in the institution. All eigenvectors in Figure 2 represented the

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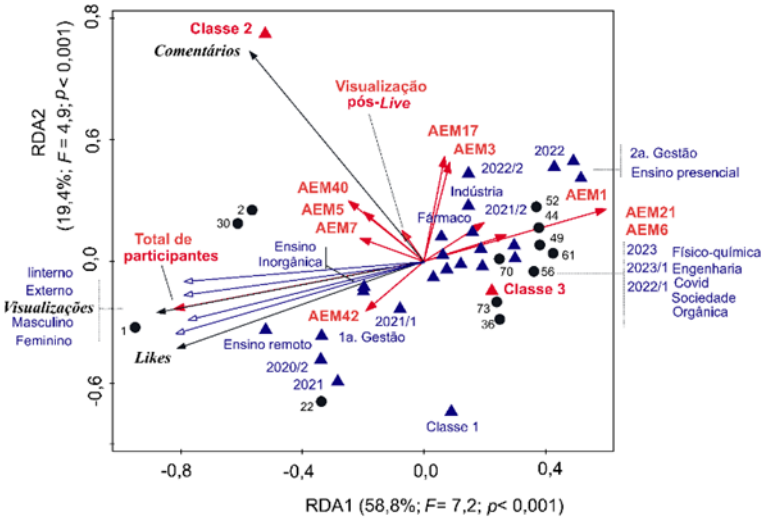
set of predictors used to explain the temporal distribution patterns of the metrics of the WebCiência IQ-UFG channel.

Successive RDA led to the selection of explanatory variables represented by the number of post-live views, the total number of participants and similarity classes 2 (high performance metrics) and 3 (low performance metrics) among the webinars, using the VIF and R2aj values as criteria. The RDA of these variables, together with the previously selected AEM, indicated strong correlations (p = 0.001) between the two matrices (R1 = 0.927; R2 = 0.839), with 80.8% (R2aj = 77.0%) of the total variation of the response matrix being explained by these predictors. The VIF values were considered low (VIF < 3.5), suggesting the absence of multicollinearity in the multivariate regressions (Figure 3).

Figure 3 – *RDA triplot* containing the performance metrics of the webinars (black arrows), predictors (red arrows) and supplementary variables (arrows and triangles in blue). Performance-adjusted webinars > 95% are represented by black circles.



Source: Prepared by the authors (2025).

According to the *triplot* in Figure 3, RDA1 (R2 = 58.8%; F-Fisher = 7.2; p = 0.001) represented strong correlations, both negative and positive, with the periods of ERE (Sá *et al.*, 2020) and return to face-to-face teaching activities at the institution, respectively. In RDA1, the channel's performance around views and *likes* was related to the total number of participants (internal and external to UFG, regardless of gender), to the webinars of the first three ERE cycles (2020 and 2021/1 cycle), associated with the themes *inorganic* and *teaching*, in addition to the first team of managers, on a mostly thin time scale (AEM40 and AEM42), while the return to face-to-face activities coincided with the second team of managers and with a multiplicity of topics, such as *physical chemistry*, *Covid-19*,

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engineering, *organic* and *society*, mostly on a large time scale (AEM1). RDA2 ($R2 = 19.4\%$; $F = 4.9$; $p = 0.001$) mainly described the similarity classes among the webinars, with those in class 2 characterized by the highest number of comments among the performance metrics, especially in the 2022/2 cycle, mainly associated with intermediate (AEM17) and large (MEM3) time scales.

Thus, while RDA1 expressed the transition from ERE to the return to face-to-face teaching, with a concomitant diversification of topics selected by the second team of managers and portrayed by the large time scale, RDA2 mostly described the performance metrics of the webinars among the similarity classes, reflected in the passage of the webinars from class 1 to class 2, Above all, due to the high count of comments on intermediate and fine time scales. Some of the aspects presented by the RDA are among the good practices suggested for the good performance of webinars held regularly in order to strengthen research and extension activities aimed at fostering collaborations between different partners. These attributes follow fundamental rules, among which the importance of the composition of the coordination team, the mapping of needs and the selection of themes for the target audience stand out, in addition to planning, organization and choice of the digital platform, among other recommendations (Fadlelmola *et al.*, 2019; Ismail; Abdelkarim; Al-Hashel, 2021).

To quantify the influence of predictor subsets, the response matrix was subjected to the partitioning of the variation explained by means of partial RDA (Peres-Neto *et al.*, 2006), reorganized into four predictor subsets: (1) the previously selected channel indicators, containing the number of post-live views, the total number of participants, and classes 2 and 3 of similarity between webinars, in addition to the eigenvectors of the (2) large, (3) intermediate, and (4) fine time scales (Figure 4A).

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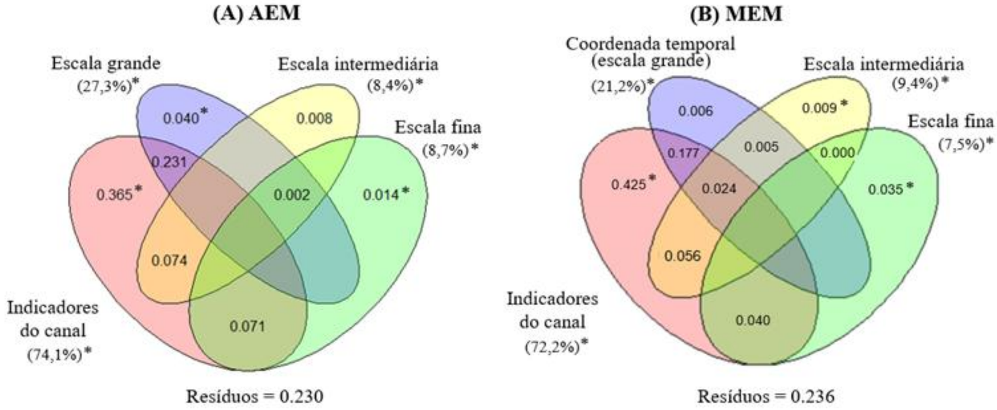
Figure 4 – Venn diagrams with the R2aj values for the pure and overlapping fractions of the explained variance according to the subsets of predictor variables: channel indicators and large, intermediate, and fine time scales of the analyses with (A) AEM and (B) MEM (Barbosa *et al.*, 2025). *$P < 0.05$.



Source: Prepared by the authors (2025).

The results indicate that the subset of channel indicators contributed to most of the total explained change (R2aj = 74.1%; $F = 50.0$; $p < 0.001$), followed by the time contribution attributed to the large scale (R2aj = 27.3%; $F = 9.5$; $p < 0.001$). The subsets of the intermediate and fine time scales contributed similarly (R2aj = 8.4% and R2aj = 8.7%, respectively) and were significant ($F > 2.8$; $p < 0.03$). When restricted to the fractions of pure variation of each predictor subset, the indicators of the channel (R2aj = 36.5%; $F = 28.7$; $p < 0.001$) and large time scales (R2aj = 4.0%; $F = 5.0$; $p < 0.001$) and fine (R2aj = 1.4%; $F = 2.4$; $p < 0.018$) resulted in significant contributions, whereas the pure fraction of the intermediate time scale, not overlapping with other subsets, was not significant (R2aj = 0.8%; $F = 1.8$; $p = 0.064$).

In a previous study, Barbosa *et al.* (2025) applied the symmetric MEM eigenfunctions, considered measures of temporal correlation (Baho *et al.*, 2015; Blanchet *et al.*, 2011), for this same dataset (Figure 4B). The trend of the time vector (large scale), represented by a subset similar to that of other predictor subsets, resulted in a non-significant fraction of pure variation (R2aj = 0.6%; $F = 2.9$; $p = 0.092$), although the total variation explained by the temporal subset was significant (R2aj = 21.2%; $F = 21.0$; $p < 0.001$), suggesting that the influence of the linear time coordinate was mainly due to the overlaps with other predictor subsets, modeled by the MEM. In fact, the symmetric nature of MEM requires that the directional trend of time be weak or absent, or when it is aimed at an evaluation of correlation, not causality, the latter related to the directionality (irreversibility) of the time vector (Baho *et al.*, 2015; Sharma *et al.*, 2011), best captured and described by the AEM.

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The statistical interpretation of the time scales, represented by the AEM, was conducted by means of linear regressions of the significant canonical coefficients of the RDA, previously validated by the normality of the residuals of the multivariate regressions with the Shapiro-Wilk test. The large time scale (r2 = 0.979; degrees of freedom (gl) = 25 and 54; $F = 98.7$; $p < 0.001$) was negatively correlated with the ERE ($p < 0.001$) at UFG, with the 2022/2 cycle ($p = 0.014$) and with the industry theme ($p = 0.030$) and positively with the years 2022 and 2023 ($p < 0.001$) and with the teaching theme ($p = 0.054$). In other words, the large time scale reflected the transition of the type of teaching at UFG (ERE to face-to-face teaching during the Covid-19 transpandemic) and the change in the management team of the extension action. The intermediate scale (r2 = 0.679; gl = 25 and 54; $F = 4.6$; $p < 0.001$) was negatively correlated with the years 2021 to 2023 ($p < 0.025$) and online and post-live *views* ($p < 0.096$). In other words, the intermediate scale captured a decrease in the channel's performance metrics as a consequence of the return to face-to-face activities at UFG, coinciding with the change in the channel's management team on YouTube®. In turn, the post-live view counts and the 2022/1 webinar cycle correlated negatively and positively, respectively, on the thin timescale ($p < 0.042$). This time scale seems to be associated with the short period of partial return that UFG went through (cycle 2021/2; December/2021 to April/2022) and that preceded the normal return of teaching activities at the institution (UFG, 2022).

In this article, the directional influence of time was adequately extracted and described by means of asymmetric eigenvectors, especially by the first eigenvector (AEM1), representing the monotonic and significant linear trend ($p < 0.001$), with a substantial portion of the explained variation (R2aj = 21.9%; $F = 21.8$) in the channel performance metrics. Thus, the elimination of directional bias in response variables, recommended with the MEM approach, since they could force the selection of alternative eigenfunctions (Bertolo *et al.*, 2012; Blanchet; Legendre; Borcard, 2008; Legendre; Gauthier, 2014; Sharma *et al.*, 2011), is not applicable with the use of AEM, because the direction of flow, often correlated with the trend, is not only known *a priori* but is also considered in the construction of directional temporal variables (Tripodi *et al.*, 2023).

Despite the particularities of the symmetric techniques, represented by the MEM, and the asymmetric technique, expressed by the AEM, in capturing and explaining the directional trend of time, the analysis using multivariate variograms through multiscale ordering (Wagner, 2004) resulted in the control of the increasing mean variance by the MSE

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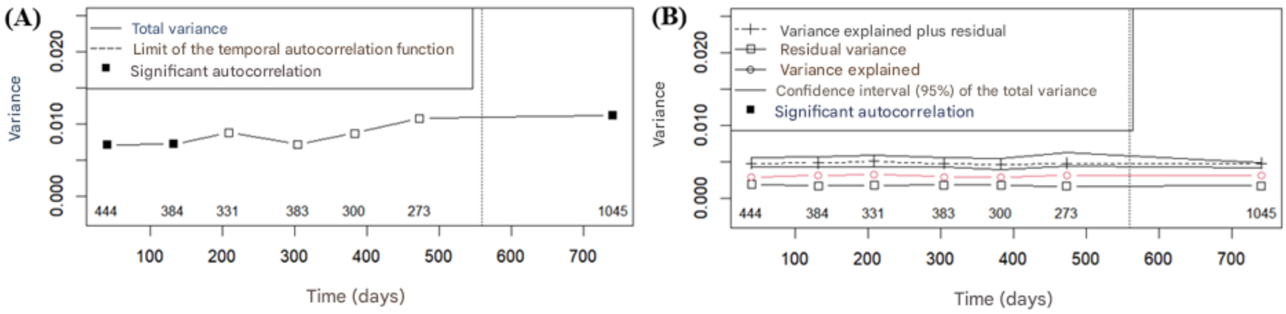
(Figure 5A), in a similar way to that previously obtained by the MEM over time (Barbosa *et al.*, 2025).

Figure 5 – Multivariate variograms (A) of the performance metrics of the webinars of the WebCiência IQ-UFG channel and (B) after the removal of the temporal structure represented by the AEM.



Source: Prepared by the authors (2025).

In the multivariate variogram (Figure 5B), no temporal autocorrelation was observed in the residuals of the multivariate regressions (RDA) and the sum of the explained and residual variances remained within the 95% confidence interval throughout the time scale. In addition, the AEM removed the trend of the increasing gradient of total variance (Figure 5A), resulting in a globally oscillating empirical multivariate variogram over time, as expected from a theoretical point of view. Thus, in addition to the AEM controlling for the increasing temporal variance in the performance metrics of the neighboring webinars, posted on the channel, they provided additional information about the directional time force ("time arrow") by meaningfully capturing the (pure) linear trend of the time vector, previously not made explicit with the use of the MEM (Barbosa *et al.*, 2025). This detailing allows the analysis of effects on performance metrics over long periods, which were not possible in the MEM approach proposed in the previous study, presenting itself as a tool for the planning of extension action and its continuity and improvement in the long term.

From these interactions, it becomes possible to optimize the content production strategy to maximize engagement. The challenges involve both the composition of the team, which requires a dedicated group of people, and the choice and alignment of themes that meet the expectations of the target audience, in addition to the planning of regular activities, participation of specialized speakers, dissemination strategies and monitoring of performance metrics for regular evaluation and analysis. With these factors, the influence of time, at different scales, allows both to explain (and predict) participation peaks and to evaluate the immediate impact and effects (in the medium and long term) of audience engagement in the channel's webinars, in order to sustain an audience, which is fundamental for the success of a scientific dissemination channel.

CONCLUSION

In this study, asymmetric eigenfunctions were adopted to detect, extract, model, and explain temporal trends at multiple scales throughout the webinars posted on the WebCiência IQ-UFG channel of the YouTube platform®. The temporal influence at different scales, represented by the AEM, incorporated the unidirectionality (irreversibility) of the temporal vector and was represented by significant canonical axes in RDA, which were partitioned into large, intermediate, and thin temporal scales. The temporal structure on the large scale was mainly related to the (linear) directionality of the temporal vector and represented the transition period from ERE to face-to-face teaching during the Covid-19 transpandemic, highlighting the impact on the institution's education system. The strategy and resources made available throughout the management of the extension action also proved to be important in engaging the public, especially regarding the previously selected themes.

The AEM modeled both the temporal influence at different scales and the increasing variance, over time, of views, likes, and comments of webinars, and allowed an advance in the understanding of how to test temporal hypotheses empirically through statistical variables and techniques that optimize the results of temporal effects associated with social media engagement. Above all, the WEAs presented themselves as a more appropriate tool for modeling in large-scale time periods, with potential applications for strategic planning of long-term extension action.

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