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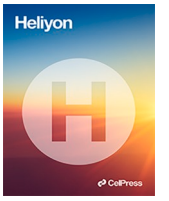

Review article

Time series analysis as an emerging method for researching L2 affective variables☆

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ABSTRACT

In language studies, marked by a myriad of psychological and social, and linguistic factors, linear modeling fails to represent the creativity, irregularity and emergent patterns of behavior. To adequately represent the dynamicity and complexity of psychological or affective variables, time-sensitive non-linear modeling is needed, especially the time series analysis (TSA), which accommodates incompatibility over time. TSA is a mathematical framework that can effectively show whether and to what degree the measured time series represent nonlinear variation through time. TSA makes prediction or retrodiction of complex and dynamic phenomena possible in future or past and, thus, can significantly contribute to the unraveling of the nuanced changes in the progress of different learner-related constructs during learning a new language. The present paper, at first, offers an introductory overview of the TSA, and then pinpoints its technical features and procedures. Exemplary works of research in language studies will be reviewed next, followed by useful conclusive remarks about the subject. Finally, suggestions will be made for further investigation of language-related affective variables using this innovative method.

1. Introduction

A standardized approach that helps to address the mathematical and statistical questions put forth by the time correlations is typically known as time series analysis (TSA) [1,2]. It is known for the extensive use of technical elements as well as mathematical procedures, including many equations (e.g., the nonlinear differential) [3]. The complex equations it involves make it hard for beginner researchers to get a complete understanding of the underlying procedures [1]. We begin with the justification for the TSA, which helps to better conceive of its distinctive features. It is not always the case that the same research participants can be traced through time. Sometimes, the researcher can gather data through time, yet not from the same cases [4]. Instances are assessments of samples on a national scale for a couple of years. A noticeable quality of TSA is its special capability of dealing with a great deal of time-sequenced observations that are equally spaced [5]. Thus, the researcher is made capable of handling a large number of data-points gathered over time [6]. Therefore, a further benefit of TSA compared to potent quantitative research methods such as latent growth curve modeling is its capability of handling easily considerably more points for data collection despite the fact that it usually employs a limited number of variables [7]. Evidently, TSA is an extremely practical research method for the line of research

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inspired by the complexity and dynamic systems theory (CDST), aiming to generate a thorough understanding of the dynamic and growing nature of an emotional, cognitive or behavioral event. It should be noted that if the time-sequenced observations are not equally spaced, latent change score modeling can be used (see Kruk et al., 2023).

If adequate points of data collection are available, the researcher becomes capable of probabilistically predicting what the future behavior of the variables will be like, as well as guessing what their behavior was like previously. This quality makes it possible to develop, test and extend theories. Considering the emphasis in CDST on the openness to context, the significance of initial states, the network of interactions, soft-assembly and complex unpredictable variation and self-organization, the power of prediction is absolutely a main way of empirically testing the theories. Basically, TSA entails collecting multiple observations to represent a time-series plot. Then, the data analysis follows in a way that diverges from the simple regression analysis, which will be different due to the issue of error term autocorrelation. In other words, in a lot of statistical processes, it is expected to randomly select the observations from a population. Nevertheless, auto-correlation occurs with the data being gathered through time, so the data cannot be considered as random anymore.

In accordance with the assumptions of complex causality and interdependence in CDST, every point of data is assimilated to the one just preceding it and the one just following it (in TSA known as serial dependence). Such a similarity defies the non-autocorrelation principle in regression analysis and in some other statistical methods, and augments the tests of significance. As a result, if TSA did not account for this assumption, researchers might obtain statistically significant findings when they are not supposed to Ref. [8].

TSA has got different modes [3]. Two of the most common are the time series regression analysis as well as the Box–Jenkins time series [8]. The former functions not much differently from structural equation modeling. Thus, specific predictions are specified beforehand and then the data are used for testing the predictability. The latter, however, follows an empirical approach. Thus, the data are first examined in Box–Jenkins time series and then a model is developed to inductively describe them. The other modes can entail a deliberate manipulation of certain variables so as to test the efficiency of an interventional program, which is also known as the interrupted time series [3].

It should be noted that the positive psychology movement and the CDST have been integrated in recent years in the SLA context (see [9]). This integration has been supported by empirical evidence indicating that students are not ergodic ensembles [10]. This means that what the average feels is not representative of the emotional experiences of each individual in the class. In other words, inter-individual variation is not equal to intra-individual variation. Thus, affective variables, based on this supporting evidence, should be no longer bound to be viewed as traits but as states which undergo changes over time [11]. Given this point, the application of the methods for the investigation of the dynamics of emotional constructs in L2 education is in its fledgling state and one of the innovative methods for this purpose is TSA.

2. Technical considerations of TSA

The best application of TSA is when what we seek to investigate, in data collection, is marked by repeated waves. We need to be capable of going back to the phenomenon we are interested in investigating and do the time-to-time measurements, or we should be able to use a database that has such data already available. For instance, we may want to examine the growth of specific dimensions of a student's L2, for example using a specific grammar rule, the tendency for code-switching or the length of T-units in the second language discourse. When the time series data are collected, we are able to plot them visually to trace the data growth trajectory. Or we can test the correlation coefficients of the divergent points of data (known in TSA as partial auto-correlation and correlo-grams of autocorrelation). The output shape might end up random, seasonal, stationary, or cyclical.

According to Shumway and Stoffer [1], the initial step in every time series research is always to carefully examine the relevant data that have been traced and plotted through time. These nuanced analyses are essential in this analytical method along with the statistical procedures used to summarize the information content of the data. It should be noted that the two different, yet not always mutually exclusive modes of TSA, are known as the time domain method as well the frequency domain method. At the heart of the former lies the examination of lagged associations, for example the way what happens today will influence what can happen the next day. The latter, however, has the examination of cycles at its core, for instance what the economic cycle will be through the expansion and recession times.

There have been certain statistical analyses developed in TSA for prediction formalization. In recent decades, some readily available technologies have been developed to collect large amounts of data intensively. Software packages have been also developed to accommodate new techniques for analysis. The most prevalent include STATA, SPSS, R, SAS, and MATLAB, with modules that can facilitate prediction. The TSA requires various statistical steps (as further described in Yazdanmehr et al., [11]). As an example, the smoothing process entails averaging the adjacent points of data to achieve what is typically known as a moving average to show how the phenomenon of interest has changed or developed through time. Additive or multiplicative seasonality may also be found in the analysis of data, which shows that a trend is raised by a definite number [3].

3. TSA in language studies

Recently more attention has been paid to human language in other fields of study including the physical sciences, with which the TSA is mainly affiliated. After significant progress made in the theory and practice of complex systems, recently it was realized that human language and language learning are a new emergent discipline for the use of methods arising from the physical sciences so as to gain a richer knowledge of language complexity [12]. Several groups of researchers have recently done valuable works of research in the area of language mathematical modeling as well as in the area of language simulations (e.g. [13–15]). A renewed interest has been

also shown in the act of unraveling and justifying structural features of languages like older studies conducted by Schwämmle [16], Havlin [17] and Zipf [18] that explored actually the word probability distribution in spoken discourse. It is noteworthy that unscrambling of the complexity inherent in language is far from easy. There is a need for employing all types of mathematical tools we have so as to gain a sound knowledge of the system of interest. The TSA is among these effective tools [19].

The existing literature using TSA is mostly related to linguistics, and less so to the psychology of language learning in applied linguistics. The reason for the analysis of some studies outside the L2 affective domain in this conceptual review is to provide the literacy required for the analysis of the dynamic fluctuations of emotional constructs in L2 education over time. As an example, Stepnicka et al. [20] presented a new linguistic approach to analyze and predict the time series. This new method mixes two elements from the classical approaches (i.e., decomposition along with auto-regression). The linguistic quality of the recommended approach is intensified by an overall need for having comprehensible and clear-cut models. In addition to the linguistic quality, Kosmidis et al. [12] emphasized that, in comparative studies, the TSA-based approach enjoyed an acceptable precision as can be comparable to the most reliable standard research methods used traditionally.

In SLA studies, as mentioned previously, the use of the TSA has been more limited. One of the earlier works of research using this method in the SLA domain was conducted by Kennedy [21]. This researcher aimed to explore how deliberate pairing affected native speakers and those non-native speakers with low proficiency in the English language in a particular multi-national and cultural pre-school in which the number of non-native speakers was three times as high as the native speakers. These researchers videotaped 4 native speakers, and used a multiple timeline design, meanwhile, they were interacting with peers within a math game's time. Ruvusky's statistic was used to test the effects of the treatment on the four interactional measures. The findings showed large differences in the case of 3 among 4 measures. Both native and non-native speakers, when paired deliberately, showed to take more turns. Furthermore, native speakers used significantly more imperatives as their non-native-speaking peers during the free-play condition. The author finally discussed the implications for English language teachers and drew attention to the role of native speakers in multi-national classrooms.

In his unpublished dissertation, Mellow [22] intended to explore the impact and effectiveness of educational tasks in improving the use of L2 English articles. This study first reviewed some issues about linguistic, psycholinguistic, pedagogical, and internal validity, and then presented the outcome of 8 longitudinal time-series case studies of adult Japanese learners of the English language. The participants lived in Vancouver, Canada. A total number of four were taught grammar directly. They also worked on input processing tasks, and output tasks about the use of articles in the English language. Mellow [22] Assessed learner development on 3 various narrative citing activities (written, spoken and cloze). The production was examined based on the particular contexts of application, pointing to the mapping of form and function which made up the students' knowledge of the interlanguage. The language learners' production of interlanguage showed the predicted variation of task, with a wider provision of on-tasks which required more attention to structure, and also the predicted variation in discourse, with the provided more continuously when it was considered as a redundant component of the writing activity and with the supplied less continuously when it was successfully omitted as a redundant component in the speaking activity. The findings also showed the changing quality of individual growth and the value of longitudinally measuring growth in different activities. Also, the findings proved to the effectiveness of the time-series approach in delineating the nuances of change through time.

In a more recent work of research, Montgomery et al. [23] argued that the investigation of SLA theory and practice can be improved by the application of the time-series research methods. These researchers introduced time-series designs as among the quasi-experiments with features that could enhance internal validity. Besides, as TSA designs just need a small number of participants, they are considered truly practical, which is a benefit to encourage more researchers to conduct empirical research of a lot of claims they make in the SLA domain, which allows for using authentic assessments which enjoy a high construct validity value. As raised by Montgomery et al. [23], the longitudinal nature of TSA also increases construct validity, which can likely lead to the production of innovative insights into how instructions can affect SLA.

The most recent related research is Jin's [24] study of the integration procedure of L2 heterogeneous instructional materials using the TSA. The procedure involved data fusion and cleaning according to the similarity measurement of the time series. This procedure employs symbol aggregation and other procedures with adjusted similarity weights to clean the data of L2 heterogeneous instructional materials. Subsequently, it employed several algorithms for heterogeneous data fusion to integrate the data. Experiments with L2 teaching materials of all proficiency levels in one city indicated that the procedure was managed to identify the abnormal data in L2 teaching materials, complete the data gap, cut down on redundant data, and do the integration process of the heterogeneous data. Having cleaned the data by using the algorithm of heterogeneous data fusion, it reflected the measurement data credibility. The mean absolute percentage error was very low. The holistic quality of data was improved, and it generated basic reliable data for using L2 teaching materials. The researcher concluded that considering the dearth of data and the existence of much wrong data in the L2 teaching materials a data cleaning method following a TSA could be effective in identifying abnormal data and making up for the missing data in L2 resources.

Though the above-mentioned SLA studies showed the effectiveness of the TSA in answering some language structural or language learning problem or question, none used the TSA to explore the dynamic innate of L2 students' affective constructs. The paper contends that as TSA has proved effective in predicting the developmental patterns of different aspects of language or the language learning process it can as well be employed in exploring language learners' affective variables.

4. Relevance of TSA to L2 affective variables

The current language studies' literatures have concentrated on the importance of different emotional constructs which could be

implicated in FLA/SLA (see [25]). Some of these, which have attracted researchers' attention more in recent years especially from a CDST approach are L2 learners' self-confidence, anxiety, different types of motivation, enjoyment, boredom, passion for learning, perseverance in learning [26], and self-reflection [27,28]. As described by Dewaele and Li [29], language studies have entered the third phase (i.e., the dynamic phase) of investigating affective variables, following the general and domain-specific phases. Following the general and domain-specific stage of emotional constructs, language studies have now begun the third phase (also known as the dynamic phase) of examining emotional factors [29]. Consideration of both positive emotional factors (such as motivation, self-confidence, grit, and enjoyment) and negative emotional factors (such as demotivation, anxiety, boredom) characterizes this dynamic shift [30]. In SLA studies, there has been a new trend toward investigating the emergence and development of emotional factors related to the learners by tracking their complex dynamic relationships [31]. This means that for the development of these factors over time and the interaction of some other factors contributing to the emergence of L2 affective variables over time, more suitable methods such as time-series analysis is needed. That is, intra-individual variation as a major aspect of L2 affective variables as complex systems is defined as variation of these affective variables over time. To estimate the intra-individual variation in these variables longitudinal intensive times series analysis is required (Michel et al., 2020).

The recent turn in the SLA studies requires suitable and innovative research methodology which are consistent with the CDST to explore L2 students' emotional aspects. Hiver and Al-Hoorie (2019) suggested a number of qualitative and quantitative research methods that can be applied to the SLA domain. Among the quantitative research methods, Hiver and Al-Hoorie [3] suggest the TSA too. Though Hiver and Al-Hoorie [3] admitted the difficulty of complicated mathematical procedures in TSA, they emphasized the prediction power of the method, and how it was appropriate to trace the fluctuation of changes in a variety of learning related constructs.

5. Typical research questions for the investigation of L2 affective constructs via TSA

A number of interesting questions can be explored using TSA, which allows a second language acquisition (SLA) researcher to predict the dynamic and complex development of different learner-related affective variables. Some of these questions can be seen in Table 1.

The exemplary questions are based on two major purposes: recognizing the quality of the sequence of data and predicting from the data on the basis of what is currently known. Nevertheless, by no means can we expect that the predictions are to be considered as deterministic in the reality of life [32]. To take a more realistic side, the model needs to be considered stochastic or better known as probabilistic and, therefore, it can be expected to be compatible with the CDST. The reason is that always there are certain potential factors involved whose origin is not known. They may add a randomness feature to the analysis. In fact, researchers using the TSA may achieve a prediction interval and estimate the probability of an observation falling within that interval.

More specifically, to address these research questions, time series analysis can be applied for the analysis and comprehension of longitudinal data regarding L2 affective variables. It should be noted that this method follows two core aims: (a) stimulating and modeling the stochastic process underlying the collected data over time and (b) predicting trends by the consideration of historical data [33]. The former is done via some techniques such as autocorrelation and partial correlation evaluation, regression analysis, and pattern recognition. The latter is estimated by the application of some other techniques such as cross-correlation evaluation and vector autoregressive (VAR) model [33]. In particular, the application of autocorrelation and partial correlation methods paves the way for the use of cross-correlation and VAR model assessment. For instance, in terms of the interaction of two L2 affective variables over time in the process of second language learning, the application of cross-correlation enables researchers to quantify the overlap between two sets of affective variables by estimating how much one set of L2 affective variables is associated with another set given the time lag between them [34]. Besides, the VAR model can be used as a multivariate time series model [33] to explore the dynamic interplay between several affective variables. These techniques can be used by Stata software program.

6. Conclusion

As pinpointed by Yang et al. [35], the different existing trends in education are worth close investigation. Different variations of TSA have been successfully used for a trend analysis of time-series data so far. TSA deals with the sort of data organized in a series of periods or intervals of time. It entails the testing of linear or nonlinear associations of several dependent variables. Education in general

Table 1
Typical research questions for the investigation of L2 affective constructs via TSA.

	TSA research questions
1	Using the present data about the current state of a certain affective variable involved in language learning (e.g., anxiety, enjoyment, boredom), to what extent can we predict how the data will appear in the future?
2	Using the present data about a particular affective variable related to L2 learners, to what extent can we guess what the data might have been like formerly?
3	How far into the past (or future) do the data which are available let us make retrodictions (or predictions)?
4	Besides the point estimated value, what is the interval or horizon prediction of what happens next?
5	How is the trend that the data on affective variables follow? Is the trend marked by linearity or non-linearity?
6	What fluctuations are represented in the data concerning the progress of a specific emotional aspects in language education? Is it cyclical, seasonal, stationary, or only random?
7	Is any causality evidenced in the pattern of a given affective variable in L2 education?

and language learning in particular entail different linear and nonlinear procedures for which TSA has been suggested for prediction purpose and has proved effective in different time-series studies [36,37]. Some other researchers (e.g., Warren, [38]) suggested that the designs using TSA can be a new replacement for traditional pretest-posttest research designs, as they are capable of identifying and testing the effects of several instructional interventions, even for small populations of students.

In SLA domain, the unpredictability of the behavior of complex systems has been recently acknowledged. The complexity rises from the fact that the present behavior is embedded within a particular background network of interactions among external and internal contexts [39]. More particularly in the case of affective factors, analyzing the snapshots of the variable (e.g., anxiety, enjoyment, boredom) of the complex system statically, or, the mere use of the probability laws to formulate hypotheses about future states or emotions fail to be informative [40]. So as to predict the directions for the development of a given affective variable, we need a record of how it has grown until the time of study. Thus, analytic procedures are needed that are capable of representing the features of the data-producing mechanism that underlie the unique observed history of the observable emotion in the learner system. These are called the idiographic time series methods [39]. Though these TSA methods have been already applied in different fields of education, in the SLA domain they have been employed less. Yet, as it was reviewed above, the existing literature point to the efficiency of this analytical framework in language studies. How TSA is relevant to the investigation of language learners' affective variables was also summarized here and some exemplary research questions were posed, to be explored in future research using the TSA. With respect to the possible implications of the use of TSA for the exploration of L2 affective variables over time, it should be noted that deeper insights into the network of factors involved in the emergence and development of a given L2 affective variable can be achieved. This further emphasizes the salience of TSA for longitudinal studies on affective variables in L2 education because most of these studies have been time-intensive and very few studies have adopted time-relation intensive methods such as TSA for this purpose within the affective domain (see [4]). Thus, via the application of TSA, L2 researchers can come up with how different factors might be incorporated in the growth of a given L2 affective variable over time.

7. Suggestions for further research

Considering the distinctive features of the TSA and the benefits it has over many traditional research methods, SLA researchers influenced by the CDST, can hope to explore different aspects of the dynamic growth of L2 learners' cognitive, affective and behavioral constructs in an L2 class [41]. They can test the linearity or non-linearity of the development of a particular variable. They can predict the future development of the variable of interest. They can speculate what its developmental patterns were like in the past. Thus, TSA allows SLA researchers to make projective or retrodictive claims about how a certain learner-related variable developed in the past and grew into its current state and how it will grow and fluctuate in future. As no L2 learner related cognitive (e.g., intelligence, field-dependence or independence) or affective variables (e.g., passion for learning, anxiety, foreign language enjoyment or boredom) have been studies so far using the TSA, each can be traced dynamically using different modes of the TSA research method. Similarly, teacher-related variables can be explored too, and possibly more complex research methods can be conceived up to trace the co-development of the teacher-as well as learner-related variables within the actual experience of classroom language learning [42, 43]. These will be all longitudinal studies that are best fitted with the dynamic and developmental nature of the variables of interest as they develop over time. The upcoming years will hopefully host more longitudinal studies of high accuracy and precision, though using small samples or even cases. The complicated nuanced underlying mathematical calculations involved in TSA add to the precision and reliability of findings. Moreover, as already suggested, for researchers interested in interventional studies, research designs using TSA might soon replace the traditional pre-test post-test designs with even small units of study (subjects) but a higher precision of analysis and reported findings [41]. It should be noted that the application of TSA for the exploration of the dynamics of affective variables in L2 education involves both learning a second and foreign language and can be expanded to the other domains of SLA such as English-medium instruction.

Author contribution statement

All authors listed have significantly contributed to the development and the writing of this article.

Data availability statement

No data was used for the research described in the article.

Additional information

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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