Open Journal of Social Sciences, 2024, 12, 664-675
https://www.scirp.org/journal/jss
ISSN Online: 2327-5960
ISSN Print: 2327-5952

Application of Time Series Analysis in Emotion Fluctuation Research

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How to cite this paper: Zhao, J. Y. (2024). Application of Time Series Analysis in Emotion Fluctuation Research. *Open Journal of Social Sciences, 12,* 664-675.
https://doi.org/10.4236/jss.2024.1211045

Received: September 30, 2024
Accepted: November 25, 2024
Published: November 28, 2024

Abstract

Research on emotion fluctuation is of significant importance for understanding human behavior and mental health. This study explores the application of time series analysis methods in emotion fluctuation research. The research first reviews the developmental history of emotion dynamics studies, highlighting the limitations of traditional cross-sectional research methods. Subsequently, it introduces the main techniques of time series analysis, including autoregressive models, moving average models, and ARIMA models. Through comparative analysis, the study evaluates the strengths and weaknesses of these methods in capturing patterns, periodicity, and trends of emotional changes. The research demonstrates how time series methods reveal the patterns of emotion fluctuation at both individual and group levels. The study also discusses the application of multivariate time series analysis in investigating the interactions between emotions and other psychological and physiological variables. However, the research also points out the challenges faced by time series analysis in emotion research, such as the continuity of data collection and the handling of measurement errors. To address these issues, the study proposes innovative data collection methods combining ecological momentary assessment and wearable devices. This research provides a new methodological perspective for interdisciplinary studies in psychology and data science, contributing to a deeper understanding of emotion dynamic mechanisms.

Keywords

Time Series Analysis, Emotion Fluctuation, Nonlinear Analysis, Ecological Momentary Assessment, Mental Health

1. Introduction

Emotion fluctuation is one of the core characteristics of human psychology and behavior, profoundly impacting individual mental health and social functioning.

Emotion fluctuation can be defined as the process of change in an individual's emotional states over time, including dynamic changes in emotional intensity, frequency, and duration (Davidson, 2015). This fluctuation may manifest as short-term emotional variations or long-term emotional change patterns. Understanding the characteristics and patterns of emotion fluctuation is crucial for psychological health research and clinical practice.

In recent years, with the advancement of psychological research methods and the development of data science technologies, scholars have increasingly recognized the dynamic nature of emotions and begun to explore more refined and dynamic research methods. For instance, the development of Ecological Momentary Assessment (EMA) has enabled researchers to collect high-frequency emotion data in natural environments (Shiffman et al., 2008). The widespread adoption of wearable devices and smartphone applications has created new possibilities for continuous emotion monitoring (Harari et al., 2016). Meanwhile, advances in machine learning and advanced statistical methods have provided powerful tools for processing these complex time series data (Jaques et al., 2015).

Traditional emotion research predominantly employed cross-sectional designs. While this approach provided important insights into the basic characteristics of emotions, it struggled to capture patterns of emotional changes over time. Research has shown that cross-sectional studies may overlook important temporal characteristics of emotional changes, leading to incomplete understanding of emotion regulation mechanisms (Kuppens & Verduyn, 2017). Time series analysis, as a powerful statistical tool, offers a new methodological perspective for studying emotion dynamics. The selection of time series analysis as the research method is based on the following reasons:

1) Time series analysis can capture the temporal structure of emotions, including trends, periodicity, and volatility, thereby deepening our understanding of emotion regulation mechanisms (Kuppens et al., 2010).

2) This method can reveal temporal dependencies between emotional states, which is crucial for understanding mechanisms of emotion maintenance and transition (Bringmann et al., 2016).

3) Time series analysis provides a statistical framework for handling continuous longitudinal data, suitable for analyzing high-frequency emotion data from new data collection methods such as EMA.

Existing research has demonstrated the broad application value of time series analysis in emotion research. For example, researchers using autoregressive models to analyze daily emotion ratings of depression patients found that patients' negative emotions had stronger autocorrelation, meaning that once negative emotions arise, they are more difficult to dissipate (Bonsall et al., 2012). Another study using Vector Autoregression models examined the dynamic relationship between positive and negative emotions, finding that positive emotions had a buffering effect on negative emotions. These findings provide new perspectives for understanding emotional regulation disorders.

This study aims to systematically explore the application prospects of time series analysis in emotion fluctuation research, assess its methodological advantages, and discuss the challenges faced in practice. We will review the basic principles of time series analysis, discuss its applications in univariate and multivariate emotion research, and introduce the latest research progress combining innovative data collection methods such as EMA. Through reviewing and synthesizing existing research, we hope to provide methodological guidance for future emotion dynamics research and promote the deep integration of psychology and data science. This interdisciplinary research approach not only helps to deepen our understanding of emotion dynamic mechanisms but may also provide empirical foundations for individualized intervention strategies in clinical practice.

2. Application of Time Series Analysis Methods in Emotion Research

2.1. Basic Principles of Time Series Analysis

Time series analysis is a statistical method specifically used to study data sequences that change over time. In emotion research, this method can capture continuous changes in emotional states, revealing patterns and regularities within them. The core assumption of time series analysis is that the current emotional state is influenced not only by the current environment but also by past emotional states. This temporal dependency can be quantified and described through autocorrelation functions (ACF) and partial autocorrelation functions (PACF). The basic models of time series analysis include autoregressive (AR) models, moving average (MA) models, and their combination form, ARMA models. AR models assume that the current emotional state can be predicted by emotional states over a certain period in the past, while MA models focus on the persistent impact of random disturbances on emotions. ARIMA models, by introducing differencing operations, can also handle non-stationary time series data, which is particularly useful for studying long-term emotional trends. These models provide us with a mathematical framework for describing and predicting the temporal dynamics of emotions. In emotion research, time series analysis can help us answer a series of important questions: How persistent are emotions? What are the differences in emotion fluctuation patterns among different individuals? How do external events affect short-term and long-term changes in emotions? By establishing appropriate time series models, researchers can quantify these characteristics and explore their relationships with mental health outcomes. For instance, research has found that emotional instability (i.e., rapid changes in emotional states) is associated with borderline personality disorder, while a decrease in emotional inertia (i.e., the persistence of emotional states) may be an early indicator of depression (Trull et al., 2015). Time series analysis also provides methods for handling missing data and irregular sampling, which are often encountered in practical emotion research. Techniques such as state-space models and Kalman filtering can be used to estimate missing observations, making the analysis more robust. Furthermore, methods like spectral analysis and wavelet analysis can reveal periodic patterns in emotion fluctuations, which is important for understanding the relationship between emotions and physiological rhythms (such as circadian rhythms).

2.2. Application of Univariate Time Series Analysis in Emotion Research

Univariate time series analysis primarily focuses on the patterns of change in a single emotion dimension over time. This method can reveal the intrinsic regularities of individual emotion fluctuations, such as the inertia, periodicity, and amplitude of emotions. By analyzing time series of daily emotion ratings, researchers can quantify the autoregressive properties of emotions, that is, the predictive ability of current emotional states for future emotions. This analysis can help identify individual differences in emotion regulation abilities, providing a basis for early diagnosis of emotional disorders. In practice, researchers often use Autoregressive Integrated Moving Average (ARIMA) models to describe the temporal dynamics of emotions. For example, a study on depression patients using ARIMA models to analyze daily emotion ratings found that patients' negative emotions had stronger autocorrelation, meaning that once negative emotions arise, they are more difficult to dissipate. This finding provides a new perspective for understanding the maintenance mechanisms of depression. Another important application is the study of emotional variability. By calculating the standard deviation or root mean square successive difference (RMSSD) of the time series, researchers can quantify the amplitude of emotion fluctuations. Studies have shown that higher emotional variability may be associated with certain psychopathologies, such as borderline personality disorder (Houben et al., 2016). However, moderate emotional variability may also reflect healthy emotion regulation abilities, highlighting the complexity of understanding emotion dynamics.

As shown in **Figure 1**, the time series of emotion intensity (blue line) exhibits clear fluctuation patterns, while the autocorrelation function (red line) reflects the temporal dependency of emotional states. This analytical method can quantify the persistence and rate of change of emotions, providing a basis for individualized emotion regulation strategies. Univariate time series analysis can also be used to study the periodic patterns of emotions. Through spectral analysis or wavelet analysis, researchers can identify periodic components in emotional changes, such as daily or weekly emotion fluctuations. These periodic patterns may reflect the regular influences of physiological rhythms or social life. For example, one study found significant differences in emotion patterns between workdays and weekends, a finding that is important for understanding the impact of work-life balance on emotional health (Ryan et al., 2010). Univariate time series analysis can also explore the immediate and delayed effects of external events on emotions. By introducing intervention analysis or transfer function models, researchers can quantify the impact of specific life events (such as stressors) on emotional trajectories. This method provides a new perspective for understanding emotional resilience and vulnerability, helping to design more targeted psychological intervention strategies.

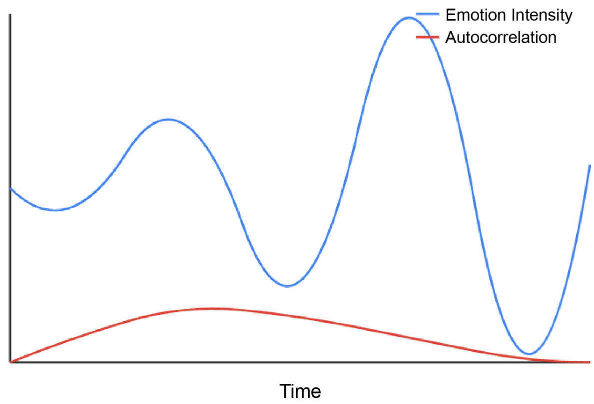

Figure 1. Emotion time series and its autocorrelation function.

2.3. Application of Multivariate Time Series Analysis in Emotion Research

Multivariate time series analysis extends univariate methods, allowing the study of dynamic relationships between multiple emotion dimensions or between emotions and other variables. This method can capture the complexity of emotional systems, revealing the interactions between different emotional components and the associations between emotions and other psychological or physiological processes. Vector Autoregression (VAR) models are commonly used tools in multivariate time series analysis. They can simultaneously consider the mutual influences of multiple variables, providing a systematic perspective for understanding emotion dynamics. For example, researchers can use VAR models to analyze the interactive dynamics between positive and negative emotions, exploring how they influence and regulate each other. This analysis can reveal the micro-processes of emotion regulation, such as the buffering effect of positive emotions on negative emotions. Granger causality testing is an important application of VAR models, which can reveal predictive relationships between variables. In emotion research, this method can be used to explore time series relationships between different emotional components, or the mutual influences between emotions and other psychophysiological variables (such as cognitive function, sleep quality). For instance, a study using Granger causality testing found that changes in sleep quality could predict emotional states the next day, while emotional states could also predict subsequent sleep quality, revealing a bidirectional relationship between emotions and sleep (Bouwmans et al., 2017).

As shown in **Figure 2**, positive emotions (blue line), negative emotions (red line), and stress levels (green line) exhibit complex interaction patterns over time. Through multivariate analysis, we can quantify the dynamic relationships between these variables, such as the impact of rising stress levels on subsequent emotional changes. Dynamic Factor Analysis (DFA) is another useful multivariate time series method that can be used to explore potential emotion dimensions. DFA combines the advantages of factor analysis and time series analysis, capable of revealing the potential structure of emotional experiences and their changes over time. This method is particularly valuable for understanding the structural and dynamic characteristics of emotions, capturing temporal patterns that traditional static analysis methods might overlook (Bringmann et al., 2016). Multivariate time series analysis can also be applied to study the relationship between emotions and physiological indicators. For example, by simultaneously analyzing time series of emotion ratings and heart rate variability, researchers can explore the dynamic associations between emotional states and autonomic nervous system activity. This type of research is significant for understanding the psychosomatic interaction mechanisms of emotions and may provide a theoretical basis for biofeedback and other intervention techniques.

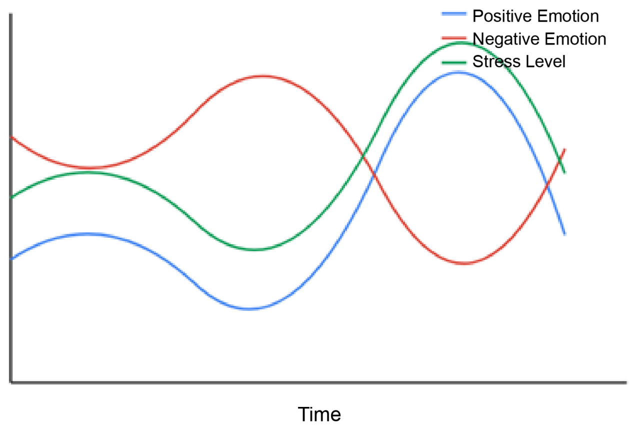

Figure 2. Multivariate emotion time series analysis.

3. Innovative Applications of Time Series Analysis in Emotion Research

3.1. Integration of Ecological Momentary Assessment and Time Series Analysis

Ecological Momentary Assessment (EMA) is a method of collecting real-time data in daily life environments, providing high-quality emotion data for time series analysis. EMA allows participants to record their immediate emotional experiences multiple times through smartphone applications or wearable devices, thus capturing natural fluctuations in emotions. This method overcomes the limitations of traditional retrospective reports and improves the ecological validity of data. Combining EMA with time series analysis, researchers can construct more refined models of emotion dynamics. For example, by analyzing the time series characteristics of EMA data, individual differences in emotion fluctuations can be identified, which is important for understanding and preventing emotional disorders. A study using EMA to collect daily emotion data from depression patients and healthy control groups found through time series analysis that depression patients had higher emotional variability and longer duration of negative emotions (Wichers et al., 2010). This finding provides new insights for early diagnosis and personalized treatment of depression. EMA also allows researchers to explore the immediate impact of contextual factors on emotions. By including environmental assessments (such as social interactions, work pressure) in EMA, researchers can use multilevel time series models to analyze how contextual factors moderate emotion dynamics. This method provides a unique perspective for understanding the context-dependency of emotion regulation. For example, one study found that the quality of social interactions could significantly predict subsequent levels of positive emotions, but this effect varied significantly among individuals.

As shown in **Figure 3**, EMA data captures subtle changes in positive emotions (blue line) and negative emotions (red line) throughout the day, as well as related contextual factors (green line). This high temporal resolution data allows researchers to conduct more refined time series analysis, revealing the complex relationships between emotion dynamics and contextual factors. The combination of EMA and time series analysis also provides a basis for personalized interventions. By analyzing an individual's emotion time series characteristics, researchers can identify early signals of emotional dysregulation and design targeted intervention strategies. For example, a study using dynamic time series models to analyze daily emotion data of depression patients discovered specific emotion patterns that predicted worsening of depression symptoms, providing possibilities for timely intervention. However, the analysis of EMA data also faces some challenges, such as handling irregular sampling and missing data. To address these issues, researchers have developed specialized time series methods, such as Continuous Time Random Walk models, which can better handle EMA data with irregular intervals (de Haan-Rietdijk et al., 2017).

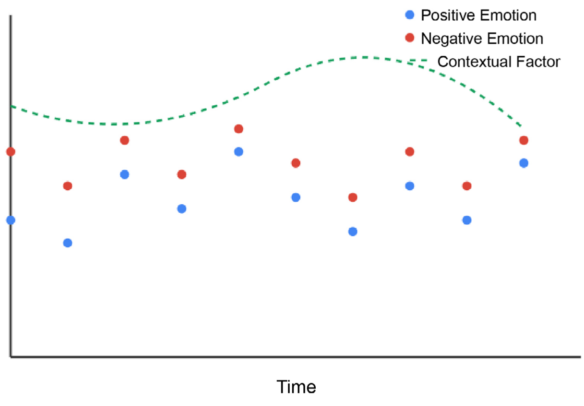

Figure 3. Analysis of emotion fluctuation patterns based on EMA data.

3.2. Integration of Network Analysis and Time Series Methods

Network analysis is a new method that has emerged in psychological research in recent years, conceptualizing psychological phenomena as networks of interrelated symptoms or features. Combining network analysis with time series methods provides a new perspective for understanding emotion dynamics. This approach not only reveals static relationships between emotional components but also captures how these relationships change over time. A major application of time series network analysis is the construction of dynamic emotion networks. In this analysis, network nodes represent different emotional states or components, while edges represent temporal dependencies between these states. By estimating time-varying network structures, researchers can explore the dynamic characteristics of emotional systems, such as how certain emotional states trigger or inhibit other states.

As shown in **Figure 4**, this dynamic emotion network depicts the temporal dependencies among three emotional states: anger, sadness, and fear. The thickness of the arrows indicates the strength of the relationship, while the color might represent the nature of the relationship (such as positive or negative correlation). This visualization method intuitively demonstrates the dynamic interactions between emotional states, aiding in understanding the complex processes of emotion regulation. An important application of time series network analysis is studying the stability and vulnerability of emotion networks. By analyzing changes in network structure over time, researchers can identify key nodes or pathways that may lead to imbalances in the emotional system. For example, a study using dynamic network analysis found that the connection strength between negative emotion nodes in depression patients increased over time, which may reflect the process of worsening depression symptoms (Snippe et al., 2017). Time series network analysis can also be used to study the effects of emotion regulation strategies. By comparing changes in network structure before and after interventions, researchers can assess the impact of specific intervention strategies on the dynamics

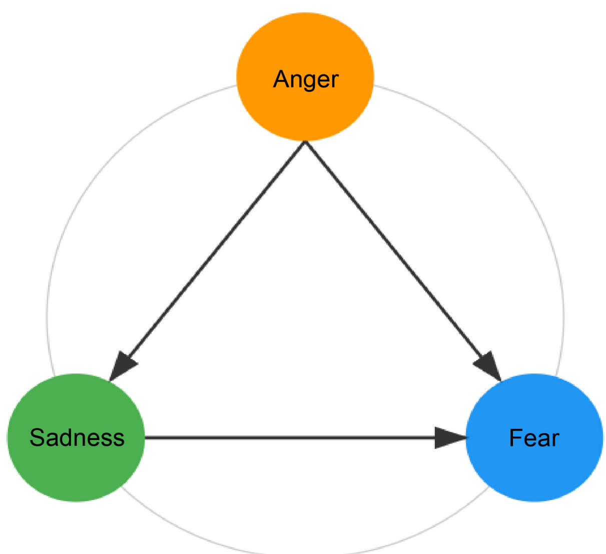

Figure 4. Dynamic emotion network based on time series data.

of the emotional system. For instance, a study using this method to evaluate the impact of mindfulness training on emotion networks found that after training, the centrality of positive emotion nodes increased, while connections between negative emotion nodes weakened (Hoorelbeke et al., 2019). However, time series network analysis also faces some challenges, such as how to handle heterogeneity between individuals, and how to capture complex temporal dynamics while maintaining model parsimony. To address these issues, researchers are developing new methods, such as multilayer temporal network models and individualized network analysis methods (Epskamp et al., 2018).

3.3. Combination of Machine Learning and Time Series Analysis

The combination of machine learning techniques and time series analysis brings new opportunities for emotion research. This fusion not only improves the predictive power of time series models but can also discover complex patterns that traditional methods might overlook. In emotion research, machine learning methods can be used for predicting emotional states, identifying abnormal patterns in emotional trajectories, and recommending personalized emotion regulation strategies. Recurrent Neural Networks (RNN), especially Long Short-Term Memory (LSTM) networks, are widely used in time series analysis due to their ability to capture long-term dependencies. In emotion research, LSTM can be used to model complex emotion dynamics and predict future emotional states. For example, a study using LSTM networks to analyze daily emotion data of depression patients successfully predicted the worsening of depression symptoms, with accuracy significantly higher than traditional time series models (Taylor et al., 2017).

As shown in **Figure 5**, the LSTM model can predict future emotional states (red dashed line) based on historical emotion data (blue line). This predictive capability not only aids in individual emotion management but may also provide timely decision support for clinical interventions. In addition to prediction, machine learning methods can also be used to extract meaningful features from complex time series data. For example, autoencoders can be used to reduce the dimensionality of emotion time series data and extract potential emotion dynamic features. These features may represent an individual's unique emotion regulation patterns, providing a basis for personalized interventions. A study using autoencoders to analyze daily emotion data from a large number of individuals successfully identified several typical emotion trajectory patterns, which were associated with different mental health outcomes (Jaques et al., 2015). Reinforcement learning techniques are also beginning to be applied in emotion research, especially in designing personalized emotion regulation strategies. By treating an individual's emotional state as the environment and emotion regulation behaviors as actions, researchers can train reinforcement learning algorithms to optimize emotion regulation strategies. This approach has the potential to develop dynamic intervention systems that can adapt to individual needs and environmental changes (Paredes et al., 2014). However, the application of machine learning methods in emotion research also faces some challenges. The first is the issue of model interpretability, which is particularly crucial in clinical applications where understanding the decision-making process of the model is essential. To address this issue, researchers are exploring explainable AI techniques, such as attention mechanisms and local interpretability methods. The second challenge is how to integrate domain knowledge and data-driven approaches to ensure that models not only have high accuracy but also reflect core concepts of emotion theory. A promising direction in this area is hybrid modeling, which combines theory-driven model structures with data-driven parameter estimation (Schultzberg & Muthén, 2018).

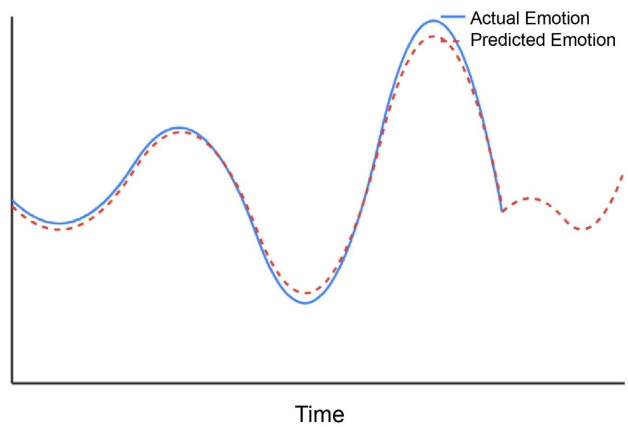

Figure 5. LSTM-based emotion prediction model.

4. Conclusion

Time series analysis, as a powerful statistical tool, offers a new methodological perspective for studying emotion fluctuations. By capturing the dynamic characteristics of emotions, this method has not only deepened our understanding of emotion regulation mechanisms but also provided an empirical foundation for designing personalized intervention strategies. The future applications of this method in emotion research can be expanded through integrating multimodal data (such as physiological indicators and behavioral data) to construct more comprehensive emotion dynamics models, developing advanced time series methods capable of capturing nonlinear and non-stationary dynamics to better reflect the complexity of emotional systems, and combining time series analysis with causal inference methods to more accurately identify causal mechanisms of emotional changes. With the advancement of data collection technologies such as wearable devices and continuous innovation in analytical methods, this research paradigm shows promise in promoting precise mental health interventions. Moreover, the integration of artificial intelligence technologies like deep learning with time series analysis may provide new solutions for emotion prediction and early warning. These technological innovations have not only promoted a shift from static, average-level research paradigms to dynamic, personalized research paradigms but also created new possibilities for the development of psychological theory and the advancement of clinical practice.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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