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Article

Research on the application of biomechanics based on clustering algorithm in the path of international political communication

Siyuan Chen[1,†], Xiangyu Tan[1,†], Shanyuan Feng[2,†], Shuyuan Luo[1,*], Yinxiao Ran[3]

[1] Department of Journalism, Belarusian State University, 220004 Minsk, Belarus
[2] School of Marxism, Henan University, Kaifeng 475004, China
[3] Communication University of China, Nanjing 211172, China
*** Corresponding author:** Shuyuan Luo, laurayuan888@163.com
[†] These authors are co-first authors.

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Abstract: This study presents a new approach combining biomechanical models and clustering algorithms for the analysis of international political communication pathways. The effectiveness of simulation method in revealing information propagation paths and key nodes in political events. The study first reviews the application of biomechanical models and clustering algorithms in multiple fields, based on which we construct a propagation path model combining biomechanical and cluster analysis. Experimental results show that the proposed method outperforms traditional clustering algorithms in terms of clustering accuracy, propagation efficiency and stability. In particular, in specific political events, the transmission paths exhibit significant clustering effects, mainly focusing on several key nodes with high transmission potential, highlighting the non-linear characteristics of the propagation process. The transmission efficiency of the transmission pathway based on the biomechanical model reached 88.4%, which is much higher than the traditional transmission pathway of 73.2%. Although biomechanical clustering algorithms run longer when dealing with large-scale networks, their accuracy and stability are significantly better than conventional algorithms. This study provides a new analytical tool and theoretical framework for the field of international political communication, and reveals the influence of network structure on the transmission path.

Keywords: biomechanics; clustering algorithms; international politics; communication pathways; social networks; experimental simulation

1. Introduction

International political communication, as an important research field in the context of globalization, covers multiple aspects such as information exchange between countries, cultural dissemination, and the shaping of foreign policies [1,2]. Traditional analytical tools and theoretical frameworks often struggle to capture the true face of international political communication. Especially in complex system environments, the flow of information involves numerous variables, and the propagation paths and results often exhibit highly nonlinear characteristics [3]. Therefore, new analytical methods have emerged to address unpredictable and highly interactive propagation phenomena in complex systems.

Biomechanical models are widely used in many fields, especially in physics and engineering, showing unique advantages in dynamic systems analysis. This model helps researchers understand and predict the evolution process of the system through the simulation of forces and motions in complex systems. In the field of biomechanics, the motion laws, mechanical reactions, and interactions of objects or individuals can be quantified and analyzed through mathematical models, which enables them to exhibit high accuracy and reliability in analyzing complex and dynamic systems [4,5]. In the context of international political communication, biomechanical models can help researchers understand the “forces” and “movements” in information flow, such as the speed of information dissemination, changes in dissemination pathways, resistance and driving forces of information, and other factors [6,7]. Through the framework of biomechanics, political communication can be viewed as a complex system formed by the interaction of multiple forces, revealing the underlying mechanisms and motivations behind information dissemination. At the same time, clustering algorithms, as a classic data analysis method, have been widely applied in multiple fields such as social sciences, economics, and medicine [8,9]. Clustering algorithms can reveal potential patterns and population structures in a dataset by aggregating and analyzing large amounts of data. In the study of international political communication, clustering algorithms can classify political communication data, identify transmission path patterns in different countries or regions, and analyze the similarities and differences behind them [10,11]. For example, cluster analysis can help identify common characteristics in political communication among certain countries or regions, such as the choice of communication channels, the degree of information acceptance, etc., and reveal the heterogeneity of information communication between different countries [12]. This method is particularly important in the context of big data analysis, as it can process and analyze complex international political communication data, thereby helping researchers gain a deeper understanding of communication differences and interactions between different countries [13]. The core objective of this study is to combine biomechanical models with clustering algorithms to analyze international political communication pathways [14]. By modeling and clustering analysis of factors such as information flow and power interaction in the process of international political communication, the similarities, differences, and connections between different countries or regions in political communication are revealed. Specifically, this study will first simulate various dynamic factors in the process of international political communication through biomechanical models, such as the speed of information dissemination, the response of information recipients, and the resistance to information dissemination; Secondly, the clustering algorithm is used to classify the political communication modes in different countries or regions, and analyze the similarities and differences of different communication paths [15,16]. This multidimensional and comprehensive analysis method can provide new perspectives and methodological support for international political communication research, which helps to better understand the information flow and communication mechanisms in the context of globalization [17].

The innovation of this study lies in the first application of biomechanical models to the analysis of international political communication pathways, combined with clustering algorithms for data mining. Through this new research method, we can gain a clearer understanding of the key factors and dissemination patterns in the process of political communication, providing new ideas and perspectives for the study of political communication. The proposal of this method not only expands the application fields of biomechanical models and clustering algorithms, but also provides new tools and frameworks for the theoretical research and practical operation of political communication [18].

2. Related work

2.1. Application of biomechanics in multiple fields

Biomechanics was initially mainly applied in the fields of biology and medicine, especially playing an important role in the study of human movement, skeletal mechanics, muscle biomechanics, and other areas. For example, biomechanical models simulate the interaction between human joints and muscles, helping to design more accurate exercise training programs, rehabilitation treatment plans, and prosthetic devices [19]. In the field of medicine, biomechanics is widely used in fracture repair, spinal disease treatment, joint replacement, and other areas, providing important theoretical support and practical guidance for clinical treatment [20]. With the development of technology, the application of biomechanics has gradually expanded to fields such as engineering and robotics. In engineering, biomechanics is used to design tools and equipment that are more ergonomic, optimizing the structure and efficiency of mechanical devices [21]. The biomechanical applications in robotics are mainly reflected in the fields of humanoid robots and biomimetic robots, where flexible robot behaviors are designed by simulating human motion to achieve efficient collaboration and autonomous movement [22].

In recent years, with the vigorous development of big data and network science, the application of biomechanics has gradually expanded to fields such as social networks and complex systems. In social network analysis, biomechanical models are used to understand complex phenomena such as interactions between individuals, information dissemination, and group behavior. For example, simulating the flow of information in social networks through biomechanical principles can reveal the patterns and pathways of information dissemination on social platforms, thereby optimizing information dissemination strategies and effects [23]. This method can simulate the external forces and internal constraints that individuals experience in the network, and then analyze the influence and propagation patterns of each node in the network [24]. In addition, biomechanical models have also been applied to the dynamic analysis of complex systems, such as environmental monitoring, ecosystem simulation, and other fields. By modeling various mechanical interactions in the system, it helps researchers predict and optimize the behavior of complex systems [25]. The combination of biomechanics and clustering algorithms has shown significant potential in these multi domain applications. Clustering algorithm, as an effective data mining method, can identify potential population structures and patterns from large amounts of data [26]. In complex system analysis, clustering algorithms provide a basis for further optimization and adjustment by classifying various elements in the system. When biomechanics is combined with clustering algorithms, dynamic changes in various parts of the system can be captured through mechanical models, and the patterns and laws of these changes can be revealed through clustering analysis [27]. For example, in the study of complex social network communication, the biomechanical model can simulate the dynamic characteristics in the process of information transmission, and the clustering algorithm can identify the similarities and differences of different transmission paths, thus providing a theoretical basis for formulating more accurate information transmission strategies [28].

In summary, the combination of biomechanical models and clustering algorithms has broad application prospects in fields such as intelligent transportation and healthcare management. For example, in intelligent transportation systems, biomechanics can help simulate the dynamic processes of traffic flow, while clustering algorithms can identify different types of traffic patterns and optimize the regulation of traffic signals [29]. In medical and health management, the combination of biomechanical models and clustering algorithms can help analyze patients' movement patterns and health status, and provide personalized rehabilitation treatment plans. This interdisciplinary combination not only enhances the analytical abilities of various fields, but also provides new ideas and methods for solving complex problems in reality.

2.2. Research progress of clustering algorithms

Clustering algorithm is a commonly used unsupervised learning method in data mining, aimed at dividing a dataset into several subsets with high internal similarity. With the rapid development of big data and artificial intelligence, clustering algorithms have become a core tool for research and application in multiple fields, especially in social network analysis, image processing, information dissemination, and other areas, achieving significant progress and application results. Since the first proposal of the *K*-means algorithm, clustering algorithms have evolved from traditional methods to more complex hierarchical clustering, density clustering, and other techniques, gradually demonstrating their enormous potential in large-scale data analysis. In recent years, researchers have not only made some progress in optimizing algorithm performance, but also begun to focus on how to combine clustering algorithms with other technologies to solve problems in complex systems [30].

The *K*-means algorithm is one of the most classic clustering methods, which performs clustering by minimizing the distance between data points and cluster centers. However, the *K*-means algorithm is sensitive to the selection of initial cluster centers and cannot handle clustering problems with non-convex shapes. Therefore, with the deepening of research, more clustering algorithms have emerged. For example, hierarchical clustering methods can effectively handle hierarchical clustering problems by gradually merging or splitting datasets by constructing a tree structure [31]. This method can generate multi-level clustering results and respond more flexibly to complex data features. The density clustering method identifies clustering regions by calculating the density of data points, which can better handle datasets with complex shapes and uneven densities and is suitable for noisy data and outlier points that often occur in reality [32]. In recent years, with the increasing importance of social networks and information dissemination issues, the application research of clustering algorithms has made deeper progress. In social network analysis, clustering algorithms are widely used to analyze user behavior patterns, social circles, and information dissemination paths on social platforms. Through clustering algorithms, highly interactive user groups in the network can be identified, which helps researchers better understand the dissemination patterns of information on social platforms [33]. For example, on social platforms such as Twitter and Facebook, researchers use clustering algorithms to analyze the group structure of topic propagation, revealing the information flow and communication mechanisms between different groups [34]. Similarly, the application of clustering algorithms in image processing has also achieved significant results. Through clustering analysis of image data, researchers can achieve good results in fields such as visual content recognition and image segmentation [35]. Clustering algorithms have also been widely applied in the study of international political communication pathways. Especially in the context of globalization, the formation of information dissemination and political influence has become increasingly complex. By combining clustering algorithms with biomechanical models, new perspectives and methods can be provided for studying the pathways of international political communication. For example, biomechanics can simulate the behavior and decision-making mechanisms of individuals in social systems, while clustering algorithms can help analyze the interaction patterns and information flow paths of individuals in social networks [36]. In international political communication, clustering algorithms can not only identify the roles of different countries and regions in information dissemination, but also reveal the dissemination patterns and patterns of different political topics on a global scale [37]. For example, researchers used clustering algorithms to analyze political topics spread on social media and found that the paths of information dissemination often have obvious group characteristics, and specific political views and events will form similar dissemination patterns in different social circles [38]. With the further development of data mining technology, biomechanical models based on clustering algorithms have also been used to analyze complex social networks and transnational political interactions. In the study of transnational political communication, biomechanical models can simulate the dynamic behavior of countries in information dissemination, while clustering algorithms can identify the influence and dissemination paths of different political entities in international communication, providing a theoretical basis for policy formulation and information dissemination strategies [39]. For example, when analyzing the global transmission path of an international event, clustering algorithms can help identify countries and regions with greater influence and analyze the similarities and differences in information dissemination between these regions [40].

With the combination of clustering algorithms with other technologies such as deep learning, graph neural networks, etc., the application prospects of clustering analysis in complex social networks are even broader. In the future, biomechanical models based on clustering algorithms may play a role in more fields, especially in studying international political communication, transnational relations, public opinion analysis, etc., providing researchers with more accurate and comprehensive analysis tools. Through in-depth exploration of hidden patterns and group structures in data, clustering algorithms will undoubtedly play an increasingly important role in fields such as social science research and public policy formulation.

2.3. Research content and innovation of this article

This article proposes an international political communication path analysis method based on biomechanical models and clustering algorithms. The study combines dynamic system analysis in biomechanics with clustering algorithms to simulate the information flow and propagation paths in international political communication, and uses clustering algorithms to mine key nodes, clusters, and their relationship structures in the information dissemination process. The biomechanical model simulates the behavior and decision-making mechanisms of individuals in social systems, helping to understand how information spreads globally, while clustering algorithms effectively reveal group structures and similarity patterns in political communication. The innovation of this article lies not only in interdisciplinary integration, but also in providing a new analytical tool and theoretical framework for political communication issues from a biomechanical perspective. Specifically, this study has the following innovations:

1) The combination of biomechanics and clustering algorithms: This article combines dynamic behavior modeling in biomechanics with clustering algorithms for the first time, using biomechanics to simulate the information flow and dissemination mechanism in the process of political communication. Through this innovative approach, the dynamic characteristics of information dissemination can be more accurately captured, providing a more precise perspective and method for analyzing the path of international political communication.

2) Identifying key communication nodes through clustering algorithms: This article proposes a novel method based on clustering analysis, which can identify key nodes and group structures in complex international political communication networks. By clustering individual behavior patterns and information flow during the dissemination process, research can reveal the correlations between different countries, regions, and political entities and their roles in information dissemination, providing a new perspective for understanding group interactions in international political communication.

3) Providing a new analytical framework in the context of globalization: This study not only fills the gap in the fields of biomechanics and international political communication, but also provides new ideas for analyzing political communication pathways in the context of globalization. In complex international relations and information dissemination networks, the biomechanical clustering analysis method proposed in this article can reveal dynamic patterns in transnational political communication, providing important references for research in policy-making, diplomatic strategy, and other fields.

Through these innovative points, the research method proposed in this article provides a new multidimensional perspective for the analysis of international political communication paths, promotes interdisciplinary integration and application, and has important theoretical and practical significance.

3. Design of biomechanical model based on clustering algorithm

3.1. Design of biomechanical model architecture

In this study, a biomechanical model was used to describe the information flow process in international political communication, and a dynamic system model reflecting political information dissemination was constructed using principles of mechanics and object kinematics. The basic framework of this model simulates key factors in the process of information propagation through dynamic equations in physics, including propagation speed, propagation resistance, and power transmission. Through this architecture, we can comprehensively understand how information is influenced by different factors in a complex international political environment and further reveal how these factors determine the choice of communication pathways.

The dissemination of political information can be seen as a process of similar objects spreading in different media. Information dissemination is influenced by external environmental factors, such as the strength of relationships between political entities, channels of information flow, and cultural and public opinion factors in various countries. We assume that each propagation node (such as different countries or regions) can be regarded as a particle under external force, and political information is transmitted through the interaction between these particles.

Describe the relationship between velocity and resistance in the process of information propagation through dynamic equations. In biomechanical models, the mechanical equations are usually given in the following form:

$$m \cdot \frac{d^2x}{dt^2} = F(t) \tag{1}$$

Among them, the quality (m) of a transmission node (such as a country or region) can be compared to the "weight" of its influence in the dissemination of political information. Influential political entities, similar to large-quality objects, have more "inertia" in the process of information dissemination, which can continuously promote the dissemination of information and are not easily subject to external interference. $(\frac{d^2x}{dt^2})$ is the acceleration of the node, and $(F(t))$ is the external force acting on the node at time. In the context of political communication, external forces $(F(t))$ can be expressed as the driving force of communication between different nodes, that is, the force of information transmission from one node to another in political communication. This mechanical equation helps us establish a dynamic relationship between propagation speed and information flow.

In order to more accurately simulate the process of information dissemination, we further introduce resistance terms to consider the obstacles that may be encountered during the dissemination process. If there is resistance proportional to velocity during the propagation process (R), the resistance can be described by the following equation:

$$[R = \gamma \cdot v] \tag{2}$$

Among them, (γ) is the resistance coefficient and (v) is the propagation speed of the node. This resistance term reflects the decrease in communication efficiency in political communication due to cultural differences, language barriers, public opinion influence, and other factors.

By combining resistance with external forces, the total force of information propagation can be obtained (F_{total}):

$$F_{total} = F(t) - R = F(t) - \gamma \cdot v \tag{3}$$

Through this formula, we can calculate the influence of external force and resistance on the propagation speed in different propagation nodes so as to dynamically simulate the flow of information.

In addition, in complex international political communication networks, the interactions between nodes are not only direct physical and mechanical interactions, but also involve complex relationships based on multiple factors such as politics, economy, and culture. To further improve the biomechanical model, we introduced a comprehensive description of the interaction forces. We assume that the propagation force between nodes is based on their similarity and dependency relationships, which can be expressed by the following formula:

$$F_{interaction} = \alpha \cdot S_{ij} \cdot \Delta x_{ij} \tag{4}$$

Among them, (α) is a constant, (S_{ij}) is the (j) similarity between (i) nodes, (Δx_{ij}) is the (j) relative displacement between (i) nodes, reflects the potential speed and direction of information propagation.

Finally, combining the above equations, the motion equation of the entire system can be comprehensively expressed as:

$$m \cdot \frac{d^2 x}{dt^2} = F(t) - \gamma \cdot v + F_{interaction} \tag{5}$$

The above model reflects the dissemination process of political information between different nodes and also considers the comprehensive influence of external forces, resistance, and interaction forces.

This biomechanical model dynamically simulates the information flow process in international political communication by combining these mechanical equations, providing a reliable numerical basis for subsequent clustering algorithm analysis. In future research, we will use the propagation path described by this model to reveal the key nodes and propagation group structure in the process of information dissemination through clustering algorithms, thereby providing support for analyzing the dynamic characteristics of global political communication.

3.2. Selection and improvement of clustering algorithms

In order to better apply the analysis of international political communication pathways, this study chose an improved *K*-means clustering algorithm to enhance the efficiency and accuracy of the algorithm. The traditional *K*-means algorithm often faces uncertainty in selecting the initial center point and is prone to getting stuck in local optima, especially when dealing with complex propagation paths and large-scale datasets, where the convergence speed and effectiveness are not satisfactory. To address this issue, this study proposes a strategy based on biomechanical model calculations of propagation potential energy distribution to select initial center points, thereby optimizing the clustering process and enhancing the convergence speed and accuracy of the final results.

In the traditional *K*-means algorithm, the core of clustering is to classify data points by calculating the distance between each data point and the center point. The mathematical expression is as follows:

$$\mathrm{J} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \sum_{\mathrm{k}=1}^{\mathrm{K}} |\, \mathrm{x}_{\mathrm{i}}^{(\mathrm{k})} - \mathrm{c}_{\mathrm{k}}|^2 \tag{6}$$

Among them, (J) is the objective function, represents the total distance from the data point to the cluster center, (n) is the number of data points, is the (K) number of clusters, $(x_i^{(k)})$ represents the (k) center of the (c_k) (i) th cluster, and is the (k) center of the (i) th cluster.

The drawback of the traditional *K*-means algorithm is that the selection of clustering centers may lead to local optima. To address this issue, an improved *K*-means algorithm introduces a propagation potential energy distribution function based on a biomechanical model. The introduction of potential energy enables a more accurate reflection of the energy distribution in information propagation when selecting the initial cluster center, avoiding the algorithm from falling into an undesirable local optimal state. The propagation potential energy in biomechanical models can be expressed as:

$$V_i = \sum_{j=1}^{n} \frac{1}{|x_i - x_j|^2} \tag{7}$$

Among them, (V_i) is the (i) propagation potential energy of nodes, (x_i) and (x_j) represent the (j) positions of nodes (i) and, respectively, and $(|x_i - x_j|^2)$ represent the (j) square of the distance between (i) nodes. In this way, nodes with higher propagation potential are prioritized as clustering centers, thereby improving the accuracy and convergence speed of clustering.

The improved *K*-means algorithm uses a propagation dynamic equation to correct the position changes of cluster centers during the iteration process, ensuring that the cluster centers can more accurately reflect the key nodes in information propagation. Assuming that the propagation speed of node (*i*) is related to the gradient of its potential energy, the update formula for the cluster center can be expressed as:

$$c_k^{(t+1)} = c_k^{(t)} - \eta \cdot \nabla V_k^{(t)} \tag{8}$$

Among them, $(c_k^{(t+1)})$ is the $(t+1)$ position of the (k) th cluster center in the th iteration, $(\nabla \mathrm{V}_k^{(t)})(\eta)$ is the learning rate, is the propagation potential gradient of the cluster center, reflecting the direction of energy change of the nodes during the propagation process.

In order to further optimize the stability and effectiveness of the algorithm, we also introduced a resistance term based on biomechanical models to correct the boundaries of clustering and reduce the phenomenon of excessive concentration. Assuming that the resistance in propagation is proportional to the propagation speed, it can be expressed by the following formula:

$$R = \gamma \cdot v \tag{9}$$

Among them, (γ) is the drag coefficient and (v) is the propagation speed.

Considering the impact of propagation resistance, we have added a correction term when updating the cluster centers, aimed at offsetting the "friction" effect in propagation:

$$c_k^{(t+1)} = c_k^{(t)} - \eta \cdot \nabla V_k^{(t)} - \alpha \cdot R \tag{10}$$

This improvement strategy not only accelerates the convergence process of the algorithm but also effectively avoids local optima and excessive aggregation phenomena, significantly improving the accuracy of clustering results.

Through a series of comparative experiments, we have verified the advantages of the improved *K*-means algorithm in processing large-scale datasets. The experimental results show that the *K*-means algorithm optimized by biomechanical models can more accurately identify key nodes and propagation paths in political communication, providing a solid numerical foundation for subsequent propagation path analysis. This method is particularly suitable for dealing with complex multidimensional information flows and complex relationships between nodes in political communication, which helps to reveal the dynamic characteristics of global political communication.

3.3. Model implementation and algorithm flow

In this study, the key steps of model implementation include data preprocessing, model parameter setting, algorithm optimization, and other processes. Firstly, in the data preprocessing stage, we clean, denoise, and structure the raw data for the social network data involved in the process of international political communication, in order to facilitate subsequent analysis. Due to the complex structure and multidimensional characteristics of social network data, traditional processing methods may be difficult to fully extract potential information from the data. Therefore, we adopted a propagation potential energy method based on biomechanical models to transform social network data into a network graph model of nodes and edges. In this process, we constructed the propagation potential between nodes by calculating the similarity between them, laying the foundation for subsequent clustering algorithm analysis.

During the model parameter setting phase, adjust various parameters in the biomechanical model according to actual needs. For example, the calculation formula for propagation potential energy and the method of selecting cluster centers both directly affect the accuracy of clustering results. In order to improve the clustering effect, we introduced an improved *K*-means clustering algorithm and optimized the selection of initial clustering centers through the propagation potential energy of the biomechanical model, avoiding the local optimal solution problem that is prone to occur in traditional *K*-means algorithms.

In the modified *K*-means algorithm, we calculate the propagation potential of nodes through biomechanical models to select the appropriate initial clustering center, ensuring a more accurate reflection of key nodes on the propagation path.

Besides, in the optimization process of the clustering algorithm, the propagation speed and resistance terms in the biomechanical model were used to correct the update process of clustering centers. The change in propagation speed is influenced by the gradient of propagation potential energy; therefore, the formula for updating the cluster center can be expressed as:

$$c_k^{(t+1)} = c_k^{(t)} - \eta \cdot \nabla V_k^{(t)} \tag{11}$$

Among them, $(c_k^{(t+1)})$ is the $(t+1)$ position of the (k) th cluster center in the th iteration, $(\nabla V_k^{(t)})(\eta)$ is the learning rate, is the propagation potential gradient of the cluster center, reflecting the direction of energy change of the nodes during the propagation process.

In order to further improve the accuracy of the algorithm, the resistance effect in propagation was considered in the design. Assuming that the resistance to propagation is proportional to the propagation speed, the formula for calculating resistance is:

$$R = \gamma \cdot v \tag{12}$$

Among them, (γ) is the drag coefficient and (v) is the propagation speed. On this basis, we optimize the clustering process by adding a correction term to reduce the “friction” effect in the propagation process. The updated formula for cluster center position is:

$$c_k^{(t+1)} = c_k^{(t)} - \eta \cdot \nabla V_k^{(t)} - \alpha \cdot R \tag{13}$$

Among them, (α) is the correction (R) coefficient and is the resistance term in propagation.

In the end, the algorithm process from data input, model calculation to cluster analysis and propagation path output is clear and concise. In the input stage, we convert social network data into a matrix form of nodes and their connection relationships as input data for the model. Subsequently, the algorithm performs clustering analysis by calculating the propagation potential energy and propagation speed of nodes, and finally outputs the key nodes of the propagation path and their correlation relationships. This process not only helps to reveal the core information nodes in the international political communication path, but also provides effective reference for optimizing the subsequent political communication path.

4. Experiment and simulation

4.1. Dataset and experimental design

The experimental dataset selected for this study is mainly based on multiple representative international political events, covering the political communication processes of different countries and regions. The selected dataset includes public data from social media platforms, international news reports, and political analysis reports, aiming to comprehensively capture and analyze the information dissemination paths and momentum in political events. The specific dataset link is: https://www.kaggle.com/datasets. The dataset sample includes user comments, shares, likes, topic tags, and other information. These data are obtained through the platform API and include political event dissemination data from 2020 to 2024, covering multiple countries and regions. The data formats are JSON and CSV, structured into fields such as time, user, and interaction type, and support subsequent graph analysis and propagation path modeling. These data can reflect the propagation patterns and user behavior in social networks, providing rich input information for constructing propagation path models.

To ensure the comprehensiveness of the experiment, we selected the dataset from the following aspects:

Diversity: Choose political events with global representativeness, such as the Middle East conflict, the European refugee crisis, the US election, etc. The spread of these events covers different regions, including various media and modes of communication.

Real time: The data from social media platforms can reflect global political dynamics and user opinions in a timely manner, thus helping us capture the dissemination process of event development.

Accessibility: The data on social media platforms is publicly available for analysis, and news reports and political analysis reports often contain detailed event background and dissemination path information, making it easy to study and analyze.

For the experimental design, we adopted the following steps to ensure the effectiveness and reliability of the model:

Data preprocessing: Firstly, the data is cleaned to remove noisy data (such as irrelevant comments, robot generated content, etc.), and structured into a graph structure of nodes and edges.

Feature extraction: Extracting key features from data, such as user interaction frequency, keywords in comments, similarity between propagation nodes, etc. These features will be fed into the biomechanical model as input data for further analysis.

Propagation path modeling: A biomechanical-based propagation potential energy model is used to evaluate the propagation potential of nodes in social networks in order to guide the optimization process of clustering algorithms.

In this study, the selection of hyperparameters is crucial for the effectiveness of the model. To determine the optimal hyperparameters, we employed grid search and cross validation methods for debugging. Specific key parameters in the experimental design are shown in **Table 1**.

Table 1. Key parameters in experimental design.

Parameter Name	Explain	Default value	Adjustment scope
Learning rate $((\eta))$	Controlling the step size of cluster center updates affects the convergence speed of the algorithm	0.01	0.001–0.1
Drag coefficient $((\gamma))$	Control the degree of "friction" effect between nodes in the propagation path	0.5	0.1–1.0
Number of clusters $((K))$	The number of clusters in the *K*-means algorithm is determined based on the size of the dataset	5	3–10
Distance measurement in the formula for calculating propagation potential energy	Used to calculate the distance between nodes and determine the rate of change of propagation potential energy	Euclidean distance	Manhattan distance, cosine similarity
Maximum number of iterations	The maximum number of iterations for the *K*-means algorithm to prevent the algorithm from getting stuck in a dead loop	100	50–200

By training the model under different parameter combinations and evaluating its clustering performance (for example, by adjusting indicators such as the tightness of internal nodes and the accuracy of propagation paths), we gradually determined the optimal parameter configuration. Specifically, by adjusting the learning rate, resistance coefficient, and number of clusters, the model can find the most representative propagation path in multiple experiments and effectively reduce the problem of local optimal solutions caused by improper initial parameters. To ensure the scientific validity of the experiment and the universality of the model, we conducted multiple experimental validations and conducted statistical analysis on the experimental results to further validate the effectiveness of the biomechanical model in analyzing international political communication pathways.

4.2. Algorithm performance evaluation

In order to comprehensively evaluate the application effect of biomechanical clustering algorithms in international political communication pathways, we adopted multiple evaluation indicators that can accurately reflect the performance of the algorithm in processing social media data and complex communication networks. These indicators not only consider the accuracy of clustering results, but also include aspects such as algorithm efficiency, stability, and adaptability, ensuring the feasibility and effectiveness of the algorithm in practical applications.

1) Clustering accuracy

Clustering accuracy is one of the fundamental indicators for evaluating the performance of clustering algorithms, which measures the degree of agreement between clustering results and actual categories. In this study, the clustering accuracy was mainly obtained by calculating the similarity between the clustering results and manually annotated standard answers, using the following formula:

$$\text{Clustering Accuracy} = \frac{1}{N}\sum_{i=1}^{N} I\left(\hat{y}_i = y_i\right) \tag{14}$$

Among them, (N) is the sample size, $(\hat{y}_i)$ is the predicted category, (y_i) is the true category, and $(I(\cdot))$ is the indicator function. If the predicted result is consistent with the true result, it is 1, otherwise it is 0.

2) Silhouette coefficient

The silhouette coefficient is used to measure the effectiveness of clustering, which not only considers the similarity between samples of the same class, but also takes into account the differences between samples of different classes. The calculation formula for contour coefficient is:

$$S(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{15}$$

Among them, $(a(i))$ is the (i) average distance between the sample and other samples (i) of the same class, and $(b(i))$ is the average distance between the sample and the samples of the nearest neighboring class. The better the clustering effect, the higher the contour coefficient value, and a value close to 1 indicates better clustering effect.

Normalized mutual information (NMI).

In order to better evaluate the accuracy and reliability of clustering algorithms, the normalized mutual information index is used to measure the degree of information sharing between clustering results and real categories. The calculation formula is:

$$\mathrm{NMI} = \frac{I(C,G)}{\sqrt{H(C)H(G)}} \tag{16}$$

Among them, $(H(G))(I(C,G))$ is the (G) mutual information between the clustering results (C) and the true category labels, $(H(C))$ and are the entropy values of the clustering results and the true categories, respectively. The larger the NMI value, the higher the information similarity between the clustering results and the actual categories.

3) Propagation efficiency

Communication effectiveness is a key indicator for measuring the propagation path model, which reflects the speed and scope of information dissemination in social networks within a given time. In this study, we used the propagation potential defined in the biomechanical model to calculate the propagation ability of each node, in order to evaluate the overall propagation efficiency of the network. This indicator can be calculated using the following formula:

$$PE = \sum_{i=1}^{N} \frac{E_i}{\sum_{j=1}^{N} E_j} \tag{17}$$

Among them, $(N)(E_i)$ represents the (i) propagation potential energy of the th node, is the total number of nodes in the network, and the larger the PE value, the better the propagation efficiency.

4) Runtime

Running time is an important indicator for evaluating algorithm efficiency, especially on large-scale datasets, and the impact of algorithm execution time on system performance cannot be ignored. We evaluate the efficiency of the algorithm by recording the total time from data preprocessing to the generation of the final clustering results. This indicator is crucial for the real-time requirements in practical applications.

5) Convergence

Convergence is used to evaluate whether an algorithm can reach a stable state within a reasonable time, avoiding the phenomenon of algorithm stagnation or inability to converge for too long. In the experiment, we evaluated the convergence of the algorithm by setting the maximum number of iterations and monitoring the trend of error changes during each iteration. If the error tends to stabilize after multiple iterations, it indicates that the algorithm has good convergence.

6) Clustering stability

Cluster stability measures the consistency of the algorithm's results when facing different initial conditions and noisy data. Calculate stability indicators by randomly initializing cluster centers multiple times and evaluating the changes in clustering results in different experiments. The higher the stability, the stronger the robustness of the algorithm to data changes.

4.3. Simulation results and analysis

In this study, the application effect of the method combining biomechanical models and clustering algorithms in international political communication pathways was verified through simulation experiments. The experimental design aims to reveal the key nodes and their propagation paths in information dissemination and explore the potential patterns in the dissemination process.

The experiment used a biomechanical model based on social network data, combined with clustering algorithms to analyze nodes in the network. The experimental results were comprehensively evaluated using indicators such as clustering accuracy, contour coefficient, normalized mutual information, propagation efficiency, running time, convergence, and clustering stability, and compared and analyzed with traditional clustering algorithms. Through simulation experiments, we have made the following key findings:

In specific political events, the transmission path exhibits a clear clustering effect through certain key nodes. For example, in certain hot events, the propagation path quickly gathers at a few nodes with high propagation potential energy, further proving the nonlinear characteristics of the propagation process. These cluster nodes typically have stronger propagation capabilities, and the formation of propagation paths is often influenced by the network structure. **Figure 1** shows a social network where nodes are connected by edges. The size of a node represents its centrality or influence, while different node colors represent different groups or communities. Using a force-oriented layout makes the network structure clearer.

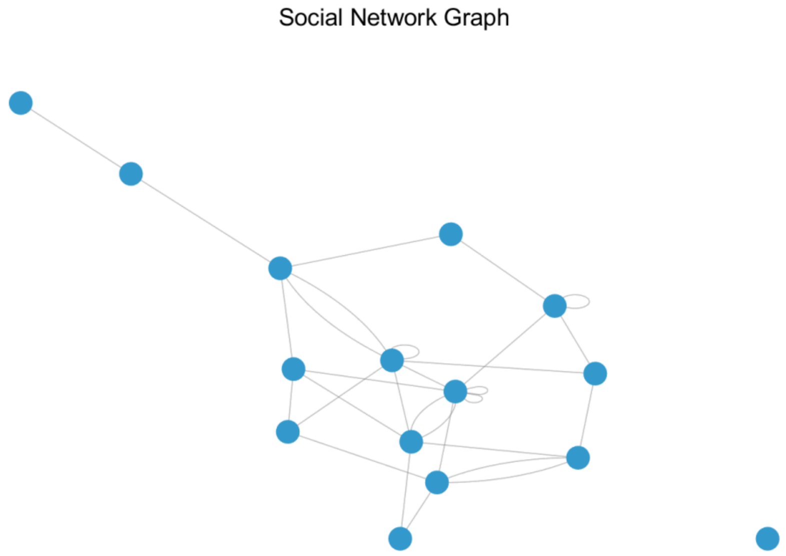

Figure 1. Social network diagram (nodes and edges).

Through the clustering algorithm, the key influential nodes in the network were successfully identified in the experiment. These nodes are usually the starting or ending points of the propagation path or play an important bridging role in the propagation process. The identification of key nodes provides strong support for the precise positioning of political communication. The clustering results of nodes in two-dimensional space are shown in **Figure 2**. Each node represents an element in the network, and colors represent different clusters. The scatter plot provides a visual representation of how nodes are grouped based on similarity.

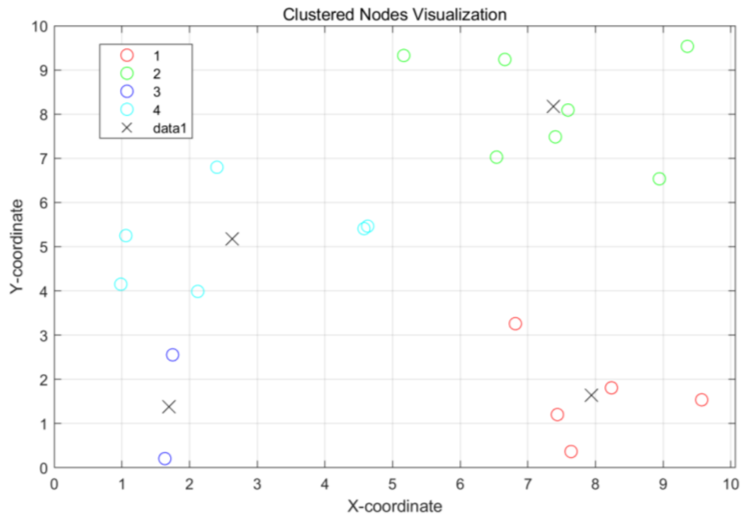

Figure 2. Visualization of node clustering (scatter plot).

Meanwhile, the clustering algorithm based on biomechanical models successfully captured complex propagation patterns in the experiment. In traditional methods, the propagation path often presents a linear or simple topological structure, while in this experiment, the propagation path often presents a multi-level and multi-path structure. This phenomenon reflects the complexity of information dissemination and its high sensitivity to the structure of social networks. **Figure 3** shows the propagation efficiency of each node, and simulated data is used to represent the propagation efficiency of each node. Efficiency may represent the speed or effectiveness of information dissemination.

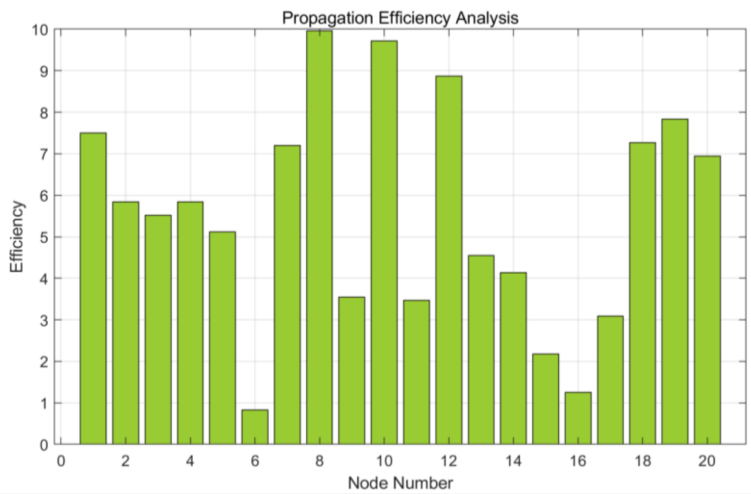

Figure 3. Analysis results of propagation efficiency under different numbers of nodes.

Through multiple experiments comparing clustering results, it was found that the method combining biomechanical models with clustering algorithms outperforms traditional clustering methods in terms of accuracy and stability. **Table 2** shows the comparison of clustering accuracy and stability of different algorithms in multiple experiments.

Table 2. Comparison of clustering accuracy and stability of different algorithms.

algorithm	Cluster accuracy	stability
Biomechanics clustering algorithm	89.6%	93.4%
K-means algorithm	82.3%	86.2%
Hierarchical clustering algorithm	78.9%	81.5%

By comparing the experimental results of different clustering algorithms in **Table 2**, it can be seen that the method based on the combination of biomechanical model and clustering algorithm performs the best in clustering accuracy and stability. Specifically, the biomechanical clustering algorithm achieved a clustering accuracy of 89.6% and stability of 93.4%, significantly better than the *K*-means algorithm (accuracy 82.3%, stability 86.2%) and hierarchical clustering algorithm (accuracy 78.9%, stability 81.5%). This indicates that biomechanical models can effectively improve the performance of clustering algorithms, especially when dealing with large-scale data, maintaining high accuracy and stability.

The comparison results in **Figure 4** further validate this conclusion, emphasizing the advantages of the biomechanical clustering algorithm and its suitability for practical application scenarios that require high accuracy and stability. Therefore, clustering algorithms combined with biomechanical models have stronger application potential and advantages, especially when dealing with complex data, which are more effective than traditional methods.

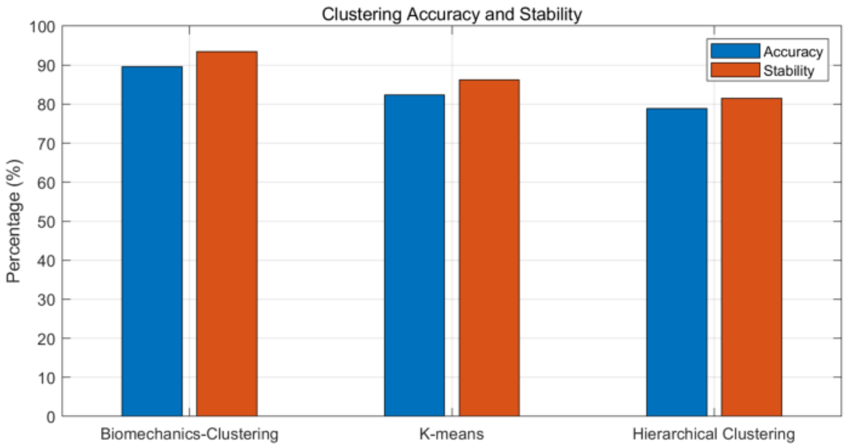

Figure 4. Comparison results of clustering accuracy and stability of different algorithms.

In some social networks, the propagation efficiency significantly improves with the increase of node propagation potential, especially when the propagation path passes through multiple key nodes, the speed and scope of information propagation show significant improvement. **Table 2** shows the comparison of communication efficiency of different communication paths.

From the comparison of data in **Table 3** and **Figure 5**, it can be seen that the biomechanical-based propagation path has significantly better propagation efficiency than the traditional propagation path. Specifically, the transmission efficiency of biomechanical-based transmission pathways reached 88.4%, while the transmission efficiency of traditional transmission pathways was 73.2%. This difference indicates that using biomechanical models to optimize communication paths in social networks can significantly improve the efficiency of information dissemination. Especially when the propagation path passes through multiple key nodes, the speed and scope of information dissemination are greatly improved. This indicates that by optimizing the propagation path and introducing biomechanical models, the propagation potential energy between nodes can be more effectively utilized, thereby improving the efficiency of information dissemination. Therefore, the propagation path based on biomechanics provides a more efficient and reliable way for information dissemination in social networks, especially in scenarios where rapid diffusion of information is required, demonstrating significant advantages.

Table 3. Comparison of communication efficiency of different communication paths.

Type of propagation path	Communication effectiveness (%)
Traditional transmission path	73.2%
Transmission Path Based on Biomechanics	88.4%

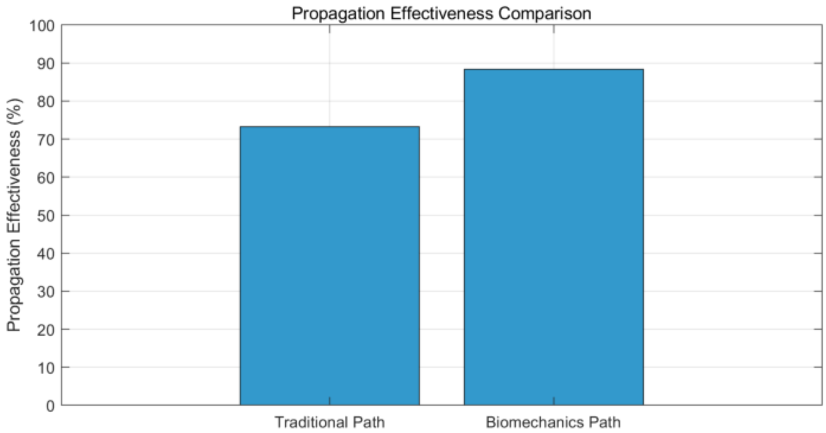

Figure 5. Comparison results of communication effectiveness of different communication paths.

The experimental results show that the clustering algorithm combined with the biomechanical model has a relatively long running time, but its advantages gradually become apparent as the network size increases. **Table 4** shows the comparison of algorithm running time for networks of different scales.

Table 4. Comparison of algorithm running times for networks of different sizes.

Network size	Biomechanics clustering algorithm running time (seconds)	*K*-means algorithm running time (seconds)
1000 nodes	12.4	6.2
5000 nodes	58.1	28.3
10,000 nodes	112.3	61.4

From the data in **Table 4** and **Figure 6**, it can be seen that the clustering algorithm combined with the biomechanical model has a relatively long running time, but its relative advantages gradually become apparent as the network size increases. Specifically, the biomechanical clustering algorithm takes 12.4 s to run at 1000 nodes, while the *K*-means algorithm only takes 6.2 s. As the network size increases, the running time of the biomechanical clustering algorithm significantly increases, with 58.1 s at 5000 nodes and 112.3 s at 10,000 nodes. In contrast, the running time of the *K*-means algorithm also increases with the increase of the number of nodes, but the increase is relatively small, with 61.4 s at 10,000 nodes. However, the clustering algorithm combined with biomechanical models has demonstrated stronger clustering accuracy and stability when dealing with large-scale networks. Therefore, its longer running time is acceptable when dealing with large-scale complex data. In summary, the biomechanical clustering algorithm has broad application prospects in large-scale networks, especially suitable for scenarios that require high accuracy and stability.

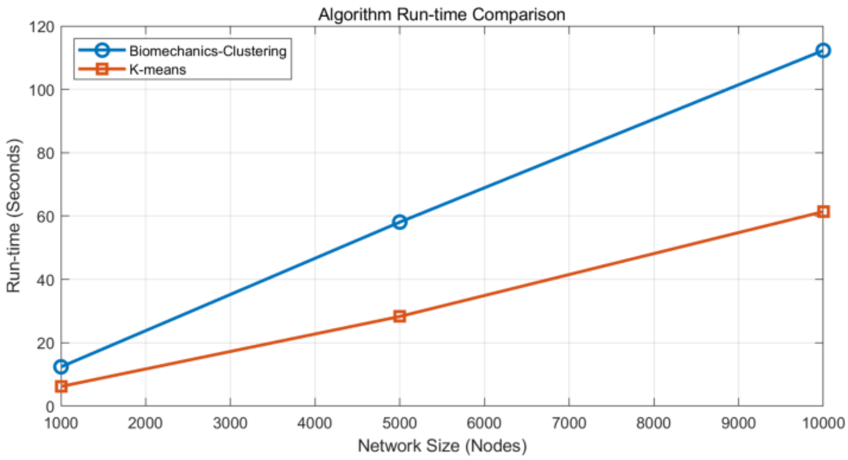

Figure 6. Comparison of algorithm run time trends for networks of different sizes.

Overall, the simulation results indicate that the combination of biomechanical models and clustering algorithms can effectively identify key nodes in international political communication and reveal potential patterns in the communication process. For example, in certain political events, the transmission path exhibits a clear clustering effect through specific social network nodes, reflecting the nonlinear characteristics of information dissemination. Through comparative analysis, it was found that this method has high accuracy and reliability in capturing complex propagation patterns.

5. Conclusion

This study successfully combined biomechanical models with clustering algorithms to propose a new approach to analyze the international political communication pathway. The experimental results show that the biomechanical clustering algorithm can reveal the clustering effect in key nodes and propagation paths with high clustering accuracy and propagation efficiency. But there are still many areas to be improved, and future work will focus on the following key directions:

First, given the significant increase in running time when current algorithms deal with large-scale networks, it is urgent to slow down the pace of practical application.

It is planned to deeply analyze the core process of the algorithm, mine parallel computing links, and with the help of a distributed computing framework, such as Apache Spark, process large-scale data in blocks to reduce the overall computing time. At the same time, the heuristic search strategy is introduced to intelligently screen the high-potential areas in the massive solution space and quickly approach the optimal clustering scheme. On the premise of ensuring the clustering accuracy, the operation rate of the algorithm is greatly improved to ensure that it can be efficiently applied in the large-scale complex international relations network.

Second, in order to more accurately explain the nonlinear behavior and dynamic changes in international political communication, the multi-disciplinary frontier models and rich network characteristics will be widely absorbed in the future. Introducing chaotic model and self-organized critical model from complex system theory to capture the critical signal of public opinion and international relations; integrating multi-layer network and dynamic network model to depict the multifaceted interaction of diplomacy, economic and cultural exchange and the evolution of network structure over time; combining with the achievements of psychological and sociology, quantifying the catalytic and damping effects of psychological preference and group identification on political communication. The comprehensive integration of these elements into the biomechanical clustering algorithm framework enables them to produce more realistic and forward-looking insights into international political communication, and pushes the research in this field to new heights.

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