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On International Chinese Education Index Ranking in a Global Perspective

Hui Chen [a], Zhengze Li [b,*], Xue Wang [a]

[a] Beijing Foreign Studies University, Beijing, China
[b] University of Göttingen, Göttingen, Germany

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ABSTRACT

The prominence of the Chinese language as a United Nations official language has sparked significant interest, leading to this research on international Chinese education (ICE). This study has a triple aim: firstly, to create indicators for monitoring ICE; secondly, to use these indicators to assess ICE development across nations; and thirdly, to highlight disparities and potential influencing factors for informed policy-making.

To facilitate indicator creation, we introduce an ICE index ranking system, evaluating 24 aspects grouped into three dimensions: Localization, Specialization, and Collaboration. These dimensions further categorize the 24 aspects into seven level-2 indicators, providing insights into global Chinese language education. After a thorough literature review and considering data availability, these indicators rank ICE in 153 countries.

For evaluation, we objectively assess indicators by assigning weights based on expert opinions. The results demonstrate that the categorized and ranked indicators offer valuable insights into global ICE development. Cluster analysis reveals diverse patterns of ICE development, with distinct areas requiring improvement across nations.

To illustrate further, we conduct a correlation analysis using an external dataset encompassing five main components: Economic Ties, Geographical Distance, Cultural Ties, Government Policies, and China's Image. The findings indicate that countries with strong economic ties to China tend to excel in all three ICE dimensions. Additionally, nations with higher numbers of tourists visiting China generally achieve higher ICE scores.

1. Introduction

The field of international education for various languages has received increasing attention from governments, language policy makers, educators, researchers, and stakeholders worldwide. Prominent examples include English, French, Spanish, Japanese, and Portuguese [1]. Among the six official languages recognized by the United Nations, Chinese language education has experienced remarkable growth, with its presence observed in over 150 countries. Approximately 80 countries have integrated Chinese into their national education systems, and more than 200 million individuals are learning Chinese as a foreign language. Notably, over 4000 educational institutions worldwide offer Chinese language courses as part of their curriculum [2]. This has something to do with the fact that Chinese is increasingly being seen as a hypercentral language that is crucial to the material success of individuals and the economic development of nation-states. (Wen Xu, 2023)However, comprehensive studies examining international Chinese education (ICE) on a global scale have been rather limited in scope and number.

A comprehensive examination of ICE has been conducted in 115 countries and selected regions, including prominent nations such as Thailand, the United States, South Korea, Malaysia, Japan, Russia, the United Kingdom, Australia, France, and Germany (B [3]. These studies have delved into various aspects, ranging from microscopic issues such as Chinese language acquisition, teaching materials, teachers, and pedagogy, to mesoscopic investigations concerning the establishment of Confucius Institutes and the development of teaching resources. Nevertheless, the existing body of research predominantly focuses on localized contexts, lacking a global and macroscopic perspective that enables the assessment of different countries using a standardized set of indicators.

This paper presents a comprehensive analysis of ICE development by collecting extensive datasets from 153 related countries. Our objective is to gain a comprehensive understanding of the status of ICE worldwide and contribute to the ongoing examination and discussion in this field. To achieve this, we introduce a novel ICE index ranking method that utilizes three categories of 24 indicators. This data-driven approach,

* Corresponding author.
E-mail addresses: chenhui@bfsu.edu.cn (H. Chen), zhengze.li@cs.uni-goettingen.de (Z. Li), 202220212029@bfsu.edu.cn (X. Wang).

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with the possibility of incorporating expert knowledge, enables a comprehensive assessment of the global ICE landscape.

The development of an ICE index ranking method holds significant importance for stakeholders involved in ICE, as it facilitates measurement, comparison, prediction, and informed decision-making. Firstly, the index ranking system allows for a meaningful comparison and evaluation of the level of Chinese language education in each country, providing valuable insights into the state of ICE. By conducting cross-country assessments, it becomes possible to estimate the overall ICE situation and determine the relative position of a particular country. Secondly, the data-driven method employed in this index enables a comprehensive measurement of ICE within a global context. It takes into account factors such as professional scale, domestic policy environment, and international cooperation and synergy. Consequently, this index serves as a valuable tool for predicting the future development trends of ICE in a given country. Lastly, the quantitative index framework presented in this study serves as an informative reference for national decision-makers, aiding in the allocation of relevant resources and identifying potential areas for improvement in ICE.

To ensure a fair and unbiased assessment of multiple criteria (indicators) in our study, it is customary to assign weights to each indicator. This allows us to calculate an indicator's score (index) by taking a weighted sum of its values, enabling us to rank them accordingly. However, the robustness and stability of a ranking method are crucial, meaning that the ranked order should remain relatively stable even with slight changes in the assigned weights [4]. To address this concern, we employ four distinct objective weight methods combining with a rank aggregation method to evaluate the ICE index across countries independently and select one the most representative as final ranking. Results show that the U.S., U.K., and Thailand rank in the top three in ICE index. In addition, we conducted a cluster analysis finding there are six different types of countries considering the countries' performance in three dimensions. Moreover, correlation studies between the ICE index ranking results and various external factors were also applied. Our analysis demonstrates a positive correlation between the three dimensions of ICE index ranking and factors such as a country's economic situation, trade relations, political landscape, educational environment and tourism, but negatively correlated to geographical distances between China and the respective countries. Localization and Specialization dimension has a single factor that is only significantly correlated with it, namely Government Effectiveness to Localization, CN's Image Score to Specialization, while no single indicator only significantly correlated to Collaboration.

The structure of the rest of the paper is as follows: Section 2 provides a review of relevant literature pertaining to the assessment of ICE and the ranking problem. In Section 3, we introduce the design of our ICE ranking system, dataset and methodology. The ranking results are presented in Section 4. Furthermore, in Section 5, we conduct a correlation analysis to provide an explanation for our ranking results. Finally, Section 6 concludes the paper, summarizing our key findings and implications.

2. Literature review

2.1. Assessment of ICE

Gil [5] examined the current global standing of Chinese as a foreign language from two perspectives: the number of students learning Chinese and the number of universities and schools offering Chinese-related programs in the US, UK, New Zealand, Australia, South Korea, Thailand, and Japan. Xiao (Y [6]. studies Chinese education in the United States by giving an overview of the National Security Language Initiative (NSLI) programs and Confucius Institute projects, the number of schools and organizations involved and the enrollments of students in these programs. Although quantitative analysis is used in these studies, the data displayed is far from exhaustive. In addition, they both focused on one specific country. Few studies have focused on comparative analysis of the situation of Chinese teaching and learning as a second or foreign language across different countries on a global scale.

The notion of "ICE index", which comprises a set of comprehensive indicators to compare the differences in the ICE development across countries in a horizontal manner, can provide a basis for policy makers' decision making to promote the development of ICE and international exchange between countries. When building the index, researchers often design indicators evaluating across multiple dimensions and aggregate them to obtain a comprehensive assessment of the overall performance (M. J [7]. For example, an "ICE Localization Development Index" [8] is constructed from 3 aspects: the integration of ICE into the national education system, the situation of Chinese language teachers and the situation of Chinese language teaching resources. Based on the assessment framework proposed in Ref. [9], which comprises 10 primary indicators and 52 secondary indicators, Wu [10] employs a hierarchical analysis method to develop an index system for assessing Confucius Institutes by analyzing the importance of each index. Wang and Han [4] present a "Global Confucius Institute Development Index" to characterize the overall development of Confucius Institutes. Wang and Chen [11] use a combination of quantitative and qualitative analysis to study the distribution of Confucius Institutes in countries along the "Belt and Road", based on the population, education, and economy data to match the national conditions of the corresponding countries. These proposed index systems provide the basis for our work in this paper.

2.2. Ranking problem

Comparing and ranking items based on various indicators is a widespread challenge as people seek to extract valuable information and make comparisons in search and recommendation systems (J [12]. For instance, when ranking universities, multiple criteria are employed to assess their academic performance, including the quality of education, faculty expertise, research productivity, and individual performance [13], Each criterion consists of several indicators. However, devising the indicators and determining a consensus ranking from them without a thorough knowledge of the various detailed indicators and their relative importance in the final ranking remains an open issue.

2.2.1. Rank aggregation (RA)

RA, or Ranking Aggregation, a procedure that merges multiple ranked lists into a more persuasive and consolidated ranking (X. [14], provides a candidate approach for addressing the ranking problem. The field of RA originated from the social choice theory (D [15]. and has found extensive applications across various domains, including information retrieval [16], marketing [17], bioinformatics [18], and university ranking [19].

Given n is the number of items $I = \{i_1, i_2, \dots, i_n\}$ and m is the number of indicators used in ranking as well as the number of ranked lists $L = \{l_1, l_2, \dots, l_m\}$, the RA problem can be defined as finding a consensus rank vector $R = \{r_1, r_2, \dots, r_n\}$ in which the r_i denotes the rank of item i_i (D [15]. Several RA methods have been proposed such as Borda's Method, Markov Chain Method, and stochastic optimization methods [20]. RA operations can be broadly categorized into two types based on their nature: *score-based RA* and *order-based RA* [21].

An example for *score-based RA* is Borda's method [22] which is considered the earliest aggregation method and a widely used benchmark in this field. In this group of RA methods, the scores of all items from multiple ranked lists are aggregated. Let $R(i)$ be the score of the item in i-th rank. The process begins by assigning a list of scores to all the rankings of n, denoted as $S = \{s_1, s_2, \dots, s_n\}$. The method then calculates the overall score for each item in the set I based on its ranking in all the ranked list L. Various aggregation functions such as sum, mean, median, or p-norm can be used. The final ranking is determined by arranging the items in the decreasing order of their total scores.

In the *order-based RA* method, the order of items is utilized as the basis. There are various ways to represent the order of items, such as rank list, a series of pairs of items, or preference matrix. For example, Markov Chain has been applied in the ranking task of webpages [16], but it requires the interaction between the items which in our case is not. What is more, graph-based methods are also applied in pairwise comparison and prediction [23–25]; L [26,27]. such as Graph Neural Networks. However, those novel methods are supervised learning which requires labeled data for the training of the models and are barely explainable either. As a consequence, the methods cannot be applied to our task directly. One potential example of order-based RA method is the Perron Eigenvector Method (PEM) [28], which generates ranking using preference matrix. The preference matrix in PEM is an $n*n$ matrix which represents the preference between each pair of items. It also contains ranking information which can be simplified to a vector. Given a set of items I and ranked lists L are given, PEM converts them to an aggregate dominance matrix $A = (a_{ij})$, and gathers the relative comparisons of the strength a_{ij} of the items i_i and i_j by

$$a_{ij} = \sum_{k=1}^{m} w_k P(\bar{r}_{kj} \succ \bar{r}_{ki}) \text{where} P(a \succ b) = \begin{cases} 1, if\ a > b \\ 1/2, if\ a = b \\ 0, if\ a < b \end{cases}$$

where, w_k is the weight of k-th indicator. Then PEM calculates the nonnegative rating vector R from A, where r_i indicates the strength or final score of i_i. However, not all the aggregate dominance matrix A is solvable for the problem at hand. Therefore, in practice, the Perron eigen value of matrix is employed, namely $Ar = \lambda r$. By using this approach, an approximation of the rating vector r can be obtained.

2.2.2. Weighting of indicators

As RA originated from social elections, considering that every voter should have an equal voting right, most RA algorithms assume that each vote carries equal weight, meaning that all input ranked lists in these RA algorithms are of equal importance Click or tap here to enter text. However, in the development of ICE ranking index differs from such traditional algorithms in the following three aspects:

1. Importance difference among indicators: Unlike the equal voting rights for everyone in electoral elections, there are significant differences in the importance of indicators in ICE rankings. Certain key indicators may carry more weight.
2. Incompleteness of data: The completeness of data is typically assumed in traditional RA ranking algorithms as incomplete votes can be viewed as invalid votes. However, considering the challenges in data collection in social science, incomplete data for some indicators are inevitable, leading to deleting the incomplete samples or resampling (H [29]. as applied in some classification tasks infeasible, because we need to keep and rank all the samples. Two prevalent approaches for managing missing values are imputation and weighting, as outlined by Ref. [30]. Although imputation can sometimes enhance the performance of machine learning models, it does not universally represent the best method for dealing with missing values [31]. Furthermore, imputation typically necessitates a presupposition concerning the cause of the missing data, such as the assumption of missing at random [32]. Therefore, considering these factors, weighting emerges as a more suitable option in our specific context.
3. Distinguishability: or the dispersion of data distribution for indicators [33]. As we convert initial indicator values into rankings, a certain degree of information inevitably gets lost. When the data distribution is highly concentrated, the resulting rankings tend to be less reliable compared to those derived from a more dispersed indicator. This is because even a slight fluctuation in highly concentrated data can induce significant changes in rankings. Consequently, the distinguishability of an indicator also impacts its importance. Indicators with overly concentrated data distributions should be assigned less weight when all else being equal.

Therefore, it is not feasible to simply calculate various indicators with equal weights. Consequently, the challenge arises when designing indicators, particularly in situations where domain knowledge is limited within a ranking system.

To address this issue, several approaches have been applied to calculate the weights of indicators based on their intrinsic attributes, including Coefficient of Variation Method (CVM), Entropy Weight Method (EWM), Criteria Importance Through Intercriteria Correlation (CRITIC), and Principal Component Analysis (PCA). These approaches provide methodologies to calculate indicator weights and address the issue of limited domain knowledge in ranking systems. By incorporating these techniques, the importance and impact of different indicators can be appropriately accounted for in the overall ranking process.

- The Coefficient of Variation Method (CVM): Coefficient of Variation (CV) is a type of relative measure of dispersion, which quantifies the dispersion of data from the average or the mean value. It is defined as the ratio of the standard deviation to the mean, as a dimensionless quantity. When the original dataset has different units for different metrics, CV can be used to make a fair comparison among them. The details of the CV method are as follows: first calculate the CV value of each index $CV_j = \frac{\sigma_i}{\mu_i}$, and then assign the weight of each index according to the CV value: $w_j = \frac{CV_j}{\sum CV}$.
- Entropy Weight Method (EWM): EWM is a popular objective method to determine the weights of multiple assessment indicators (L. H [34]. Different from CVM using CV as weights, EWM sets weights for each indicator by each indicator's entropy. A larger entropy means the indicator is more important and the weight is higher. The entropy values of indicators are in inverse proportion to their entropy weight; if the data of one indicator vary substantially (i.e., that indicator can provide much useful information), its entropy would be low, and its entropy weight would be high.
- Criteria Importance Through Intercriteria Correlation (CRITIC): The CRITIC method is another weight method [35]. It employs correlation analysis to calculate the contrasts between criteria, based on the standard deviation of normalized criterion values by columns and the correlation coefficients of all pairs of columns [36]. Like EWM, original data also needs to be standardized using Min-Max normalization, and then each column vector is recorded as y_i; the standard deviation of each column is recorded as σ_i; the linear correlation coefficient between vectors is calculated and recorded as r_{ij}, resulting in a symmetric matrix of size $m*m$. Then calculate a measure of the conflict created by criterion j with respect to the decision situation defined by the rest of criteria $\sum_{k=1}^{m}(1 - r_{jk})$, then determine the quantity of the information in relation to each criterion, namely $C_j = \sigma_i * \sum_{k=1}^{m}(1 - r_{jk})$. Then the final weight for indicator j can be calculated by normalizing these values to unity according to the following equation: $w_j = \frac{C_j}{\sum_{k=1}^{m} C_k}$.
- Principal Component Analysis (PCA): The PCA method is a technique which transforms a high-dimensional dataset into a low-dimensional one and removes redundant information [37]. It can identify the most important metrics for an index and derives the linear relationship between metrics by extracting the most relevant information in the dataset. PCA also requires Min-Max normalization of the data before use. The first five eigenvectors of the matrix $\{A_1, A_2, \ldots, A_5\}$ are calculated and the coefficients are weighted according to their variance contributions to obtain the weights C_j are calculated and the coefficients are weighted by normalizing these values too: $w_j = \frac{C_j}{\sum_{k=1}^{m} C_k}$.

2.3. Ranking Aggregation for ICE index ranking

This paper focuses on utilizing weighted RA methods for ICE index ranking, which is an unsupervised problem due to the lack of consensus on indicator definitions and a ground-truth ranking for ICE. Unlike conventional RA operations in social election, the input data for ICE consists of raw values for all indicators, rather than a pre-determined ranked list from experts or voters. Considering what was mentioned earlier, several challenges and practical considerations need to be addressed in this context. These challenges include the following:

- Missing Values: Due to the difficulty in collecting raw data for ICE indexes, the ranked lists of ICE indexes may contain missing values. Dealing with missing data and ensuring the RA method is robust to such missing values becomes crucial.
- Multi-Level of Measurement: The ICE indexes encompass diverse levels of measurement. While some indexes are numeric (e.g., 'No. of universities offering Chinese majors'), others are Boolean (e.g., 'Whether Chinese is included as part of education systems') or ordinal (e.g., 'Level of ICE in syllabus'). The RA method needs to accommodate and handle rankings derived from all levels of measurement data.
- Reweighting of Indexes: Due to the lack of consensus on the exact definition of ICE items/indexes, conventional RA methods assume equal weighting for all indexes. However, considering the presence of missing values and different levels of measurement, the information derived from each ranked list may vary. Therefore, the ability to reweight the indexes becomes necessary. The RA method should support both automatic and manual reweighting of the indexes.

These specific challenges highlight the need for robust handling of missing values, flexibility in accommodating different levels of measurement, and the ability to reweight the indexes based on the available information. Addressing these challenges will enhance the applicability and effectiveness of RA methods in ICE index ranking.

As shown in Table 1, not all the RA methods are applicable for the challenges. To achieve a consensus rank from a series of indicators in multi-level-measurement raw data, a new approach needs to be built.

3. ICE index system, dataset and method

Based on the related work mentioned in §2.1, we attempting to assess the current ICE situation in countries around the world from 3 dimensions: the degree of specialization, the degree of localization and the degree of collaboration with China. And refine them into 7 level-2 indicators and 24 level-3 indicators as shown in Table 2(efer to §3.2).

3.1. Choice of indicators

This paper introduces "International Chinese Education Development Index" (ICE-DI) as a tool for evaluating, analyzing, and comparing the development of ICE in different countries. The ICE-DI has been developed by a team of five faculty members from Beijing Foreign Studies University, each with a research focus on ICE spanning 18–40 years. The selection of indicators for the index is guided by two general principles.

Table 1
Applicability of methods (✓: applicable, -: applicable under assumptions, ×: not applicable).

	Missing Value	Multi-level-of-measurement	Reweighting
Bordas method	–	×	×
CVM/EWM/CRITIC/PCA	–	✓	×
PEM	✓	–	✓

- C*ombination of comprehensiveness and representativeness.* This means that indicators are chosen to consider not only the independent development of ICE within a country but also its development in collaboration with resources from China. For instance, when measuring the development of ICE in a country, indicators should include factors such as the availability of domestic textbooks and the number of universities offering Chinese majors, as well as the proportion of these universities in relation to the total number of universities in the country. To ensure comprehensiveness, the number of students majoring in Chinese and the number of local learners in each country are selected as indicators of the scale of learners. However, since the latter already includes the former, only the latter is chosen to represent this aspect.
- *Ensuring data coverage.* Indicators with high data coverage are preferred over those with limited availability. For example, while Massive Open Online Courses (MOOCs) are significant teaching resources, they are only produced locally for ICE in a few countries, resulting in rather low data coverage. Therefore, the number of MOOCs is not chosen.

Drawing upon principles identified in §2.1, as well as previous index systems, relevant reports, and papers (refer to §2.1 for detailed sources), we propose an International Chinese Education Index System. The candidate indicators are selected based on their relevance to ICE and the availability of relevant data resources. The index system consists of three dimensions (Localization, Specialization, and Collaboration) as level-1 indicators. Each dimension encompasses three level-2 indicators, which are further refined into 24 level-3 indicators, as presented in Table 2 in §3.2. The selection of indicators considers both the current state of ICE, such as the availability of ICE courses, and its sustainable development, such as the number of scholarship/award-winning ICE teachers who are selected and sent to China for training to become qualified local Chinese teachers, indicating the potential growth of local professionals in the field. As such, the proposed index system aims to provide a systematic assessment of the current level, growth potential, and international development of ICE from diverse perspectives.

3.2. Dataset

The data in this article was collected by more than 100 faculty members and graduate students from BFSU between April 2022 and June 2023. Despite our efforts to build a comprehensive database, the issue of missing values still persists due to the challenges in data collection. In order to emphasize the significance of data coverage in our index system and to effectively assess the quality of data, we have incorporated a key indicator called "data completeness". This indicator and other descriptive statistics are presented in Column 4 of Table 2. Here, data completeness is defined as $Completeness = 1 - \frac{number\ of\ missing\ values}{number\ of\ items}$. Data completeness is evaluated based on two aspects: indicator data and national data. Indicator data completeness reveals that Collaboration has the highest percentage (98.7 %), followed by Specialization (36.5 %), while Localization demonstrates the lowest completeness rate (31.7 %). Challenges in achieving data completeness arise from specific indicator attributes, some of which remain difficult to perfect despite their theoretical significance. For example, accurately determining the precise count of local Chinese teachers poses challenges. Additionally, inadequate research on ICE contributes to the lack of available nationalized data on ICE apps.

National data completeness refers to the degree of data completeness for different countries, as measured by the indicator-wise approach. The level of data completeness varies among countries, with fifty countries of them achieving a completeness rate above 50 %, while the remaining countries fall within the range of 33 %–50 %. Among the 153 countries

Table 2
International Chinese education development index system and statistics.

Level-1 Indicators	Level-2 Indicators	Level-3 Indicators	Data completeness			Data Sources
Localization [8] (Weight:40 %)	Education Policy	Whether a formal assessment syllabus has been issued or Chinese language grade is included as part of the university selection criteria	43 %	49 %	32 %	CNKI (https://www.cnki.net); Duxiu Knowledge Base (https://www.duxiu.com); Chinese Language Globalization Database; official websites of the ministries of education of various countries and provinces/states
		Whether there is an official institutional setup and its guarantee system	75 %			
		Whether Chinese is included as part of education systems	91 %			
		Whether ICE is included in standard Chinese education in national education system	42 %			
		Which level of foreign language does ICE belong to	29 %			
		Level of ICE in syllabus	16 %			
	Local Teachers	No. of local Chinese teacher	11 %	11 %		official websites of the ministries of education of various countries and provinces/states; International Chinese Education Research Report; The Yearbook of Chinese Education in the World; Chinese Language Globalization Database
	Teaching Resources	No. of ICE websites	19 %	11 %		Chinese Language Globalization Database; Microsoft Bing; Google; Baidu search and web crawling; People's Daily Online (http://www.people.com.cn); Global Times (https://www.huanqiu.com); Xinhua net (http://www.news.cn)
		No. of local ICE textbooks	12 %			BFSU Global Multilingual Textbook Resource Center Database; International Chinese Language Teaching Resources Development Report; Center for Language Education and Cooperation
		No. of ICE Apps	9 %			Apple App Store; Google Play; Huawei App Gallery
		No. of ICE related publishing presses	3 %			BFSU Global Multilingual Textbook Resource Center Database; International Chinese Language Teaching Resources Development Report
Specialization [38] (Weight:35 %)	Professional Develop-ment	No. of published academic papers	49 %	24 %	37 %	CNKI (https://www.cnki.net); Web of Science (http://webofscience.com/)
		No. of universities offering Chinese majors	16 %			CNKI (https://www.cnki.net); Chinese Language Globalization Database; official websites of colleges and universities in various countries; authoritative higher education information websites; authoritative higher education information websites such as UCAS.COM
		The percentage of universities offering Chinese majors	16 %			
		Level of tertiary training (BA/MA/PhD)	16 %			
	Scale of Develop-ment	No. of learners enrolled in Confucius Institutes (2020)	99 %	53 %		Center for Language Education and Cooperation (http://www.chinese.cn/); Confucius Institute Annual Development Report
		No. of ICE specialized organizations	16 %			Chinese Language Globalization Database; The International Society for Chinese Language Teaching (http://www.shihan.org.cn); official websites of the ministries of education of various countries and provinces/states
		No. of ICE learners	45 %			Chinese Language Globalization Database; International Chinese Education Research Report; The Yearbook of Chinese Education in the World
Collaboration [39] (Weight:25 %)	Collabora-tive Communi-cation	Level of board members of the International Society for Chinese Language Teaching	99 %	99 %	99 %	Official websites of the ministries of education of various countries and provinces/states
		No. of official cooperative education agreements	99 %			Ministry of Foreign Affairs of the People's Republic of China (https://www.fmprc.gov.cn); International Chinese Language Education Talents (http://zhaopin.jiaohanyu.com/company/c_show-id_2218.html); Language Education and Cooperation Annual Report (2017–2022)
		No. of collaborative academic conferences	99 %			Official websites of relevant event organizers
	Collabora-tive Cultivation	No. of ICE teachers sent from China (2019)	99 %	99 %		Chinese International Education Foundation (https://www.cief.org.cn)
		No. of Confucius Institutes (2020)	99 %			Center for Language Education and Cooperation (http://www.chinese.cn/); Confucius Institute Annual Development Report
		No. of ICE teachers sent to China for training (2018)	99 %			Chinese International Education Foundation (https://www.cief.org.cn)

analyzed, Australia has the highest data completeness rate (89.74 %), followed by Russia and Thailand (84.62 %), whereas Luxembourg has the lowest rate (33.33 %). These variations in data completeness may be influenced by factors such as the importance of ICE in the specific country, country's economic strength, quality of the internet system, and development of public media within each country.

The observed differences or disparities in data completeness among countries have significant implications for selecting methodologies and shaping the future direction of ICE data research. These variations underscore the importance of considering and addressing disparities in data completeness when examining factors that contribute to such differences. Understanding them can guide researchers towards developing more comprehensive and reliable approaches to collecting and analyzing ICE data.

3.3. Method

To overcome the challenges mentioned in §2.3 and make it feasible to derive the final rankings from the initial numerical values while still allowing for manual weight assignment, we have integrated the manually weighting, automatic weighting (CVM/EWM/CRITIC/PCA) and PEM methods. To begin, utilize automated weighting methods to determine the weightings of level-3 indicators, considering this as the relative significance of each feature. By expert discretion, we assign weights to the level-1 indices: Localization, Specialization, and Collaboration, with values of 40 %, 35 %, and 25 % respectively. Then, adjust the weights of the level-3 indicators in accordance with their importance, ensuring that the aggregate weight of the level-3 indicators grouped by their corresponding level-1 index aligns with the given distribution of 40 %, 35 %, and 25 %. Lastly, transfer these adjusted weights to the approximation algorithm (PEM) to compute ICE rankings. For the ICE development, Localization is the main goal, and Specialization is a higher goal that can only be achieved after a certain degree of Localization has been reached. From a practical point of view, the support of a language's home country has a massive impact on the spread of the language, especially in countries where there is a large shortage of local Chinese teachers and local teaching resources, and teachers and resources from China can play a significant role in supporting the development of local Chinese language education. Collaborative support from the home country can be found in the global spread of any language, such as the British Council of the U.K., the Alliance Française of France, the Goethe Institute of Germany, the Instituto Cervantes of Spain, and the Dante Institute of Italy. The selection of automatic weighting method will be discussed in §4 and the explanation will be discussed in §5.

This combination is qualified to the challenges since:

1. For Missing values: The CVM and EWM weighting methods and PEM are applicable when inputs containing missing values. It is also applicable for CRITIC and PCA methods after filling the missing values with zeros.
2. For multi-level of measurement: PEM apply the preference matrix rather than raw values can get rid of the influence from different measurements and different order of magnitude. And the information lost during converting raw values to preference matrix can be partly compensated by automatic weighting method which can extract the distribution pattern of level-3 indicators and weight the indicators with higher discrimination more. What is more, proper preprocessing also helps.
3. For reweighting ability: The employment of manual hard limits on level-1 indexes serves to incorporate human input into the ranking system. This strategy is able to control the ratio of three level-1 indexes by human knowledge keeping over-detailed level-3 indicators' weights flexible, otherwise the weights could be imbalanced due to disproportionate numbers of level-3 indicators.

Practically, we preprocessed all available data for all indicators for all countries in our database as follows:

1. Manually categorize the raw data whose distribution extremely skewed, such as No. of ICE learners.
2. Rescale the raw data to range from zero to one by Min-Max normalization to unify the order of magnitude of indicators.
3. Filling in missing values with "0″ only for calculating the weights by CRITIC and PCA methods.
4. Preset the weights of level-1 indicators are given based on ratings of a pool of six senior experts (Localization/Specialization/Collaboration: 40/35/25)

After the rank data cleaned and ready to rank. First, we use four different weighting methods to calculate the indicators weights and deliver the weights to PEM to get the final ranking as mentioned. The whole data processing flow is shown as Fig. 1 below.

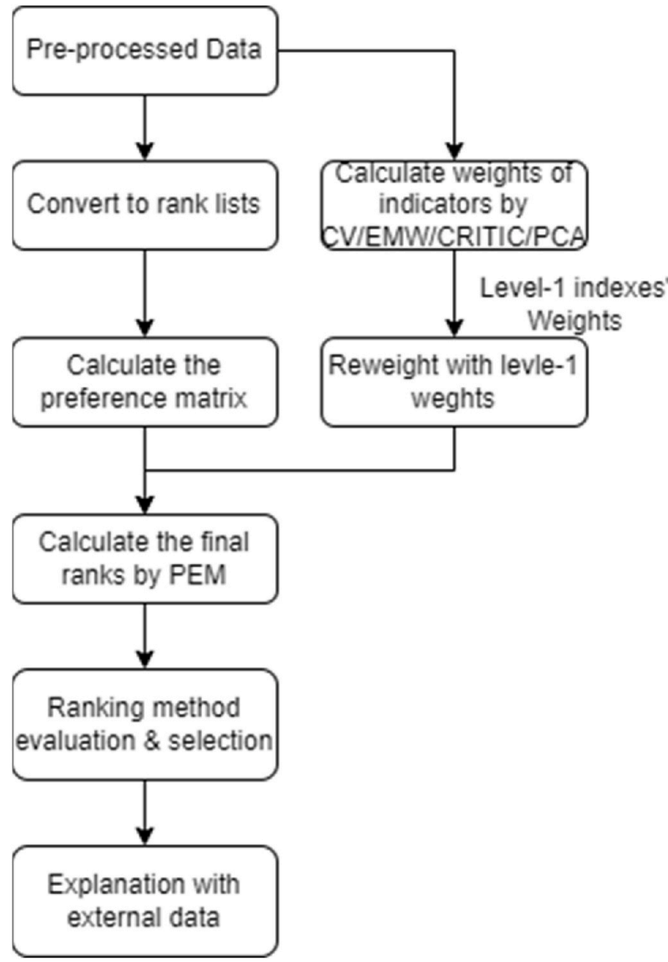

Fig. 1. Data processing flowchart for our RA methods.

4. Results

Table 3 displays the top 20 countries for each combination of ranking methods. In order to determine the best ranking method, our strategy is to choose the most representative ranking. This entails selecting the

Table 3
20 Top ranked countries.

Rank	CVM + PEM	EWM + PEM	CRITIC + PEM	PCA + PEM
1	United States	United States	United States	Thailand
2	United Kingdom	United Kingdom	United Kingdom	United States
3	Thailand	Thailand	Russia	South Korea
4	Australia	Russia	Thailand	United Kingdom
5	Russia	Germany	Germany	Australia
6	Germany	Australia	Australia	Indonesia
7	South Korea	South Korea	France	Russia
8	France	France	South Korea	Egypt
9	Canada	Japan	Japan	Italy
10	Japan	Canada	Italy	New Zealand
11	Italy	Spain	Indonesia	Pakistan
12	Spain	Italy	Spain	Canada
13	Indonesia	Indonesia	Canada	Madagascar
14	New Zealand	Mongolia	Portugal	Spain
15	Egypt	Portugal	Mongolia	Malaysia
16	Mongolia	Egypt	Malaysia	Myanmar
17	Malaysia	New Zealand	Egypt	Laos
18	Portugal	Malaysia	New Zealand	Germany
19	Laos	Laos	Cambodia	France
20	Cambodia	Cambodia	Laos	Ukraine

ranking that exhibits the highest similarity to all other rankings.

From Table 3, we can discern a significant discrepancy between the results obtained from the PCA method and the other three methods, leading to its initial exclusion. Among the remaining methods, we proceed to calculate Kendall's Tao Distance pairwise and take the average of each method, as illustrated in the table. Kendall's Tao Distance is a method for calculating the distance between two sets of rankings, with a smaller value indicating greater similarity which could be calculated by the equation: $K(r_1, r_2) = \sum K_{i,j}(\sigma_1, \sigma_2)$ where $\sum K_{i,j}(\sigma_1, \ \sigma_2) = \begin{cases} 0 \mathit{if\ item\ i\ and\ j\ remains\ same\ order} \\ 1 \mathit{if\ item\ i\ and\ j\ remains\ opposite\ order} \end{cases}$ (Chatterjee et al., 2018). The average Kendall's Tao Distances are 0.608, 0.616, 0.612 for CVM, EWM, and CRITIC, respectively. Thus, CVM ranking is regarded as the most representative ranking result. The rank result of top 3 countries from different continents and the top 20 countries are shown in Table 4 and Table 5. In the following part, the ranks used would be CVM ranking by default.

Other countries are ranked in the form of following ranges: 21–50, 51–100, and 101+. The detailed listwill be released publicly soon.

Noteworthy that most of high ranked countries are from Asia-Pacific/Pacific Rim region; their closer geographical distance to China is a probable reason. Since a closer geographical distance means higher interaction possibility such as trade and tourism, leading to a higher need of communication and language learning. Those topics will be further discussed in §5.

During the data analysis approach, we found that there could be a huge gap between the ranks of three level-1 indicators even within the same country. To find the patterns between ICE level-1 indicators' ranking and overall ranking distribution varies across countries, K-Means algorithm and radar charts are applied for clustering analysis [40] and the partial results are shown by radar charts. As a commonly used tool to visualize the cluster, a radar chart consists of a sequence of equip-angular spokes, with each spoke representing one of the ranking of indicators in our case. The farther away the central point, the higher the ranking. Lines are drawn connecting the rankings for each index. Six typical clusters are detected and their indicators' ranking distribution with cases are shown in Fig. 2 below. The number of cluster K is decided by Silhouette Analysis method (https://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_silhouette_analysis.html). Before clustering, a simple transformation is made to rescale the ranks to a relative value, namely let each level-1 index rank divided by the average of three level-1 indexes rank. The smaller value indicates the country performs relatively better in the index compared with the three indexes' average. The result shows that six typical indicators' ranking distribution cases are clustered by K-Means method.

The clustering result shows the relationship among the level of the three dimensions within each country indicating that countries have inconsistent levels of Specialization, Localization and Collaboration, and each type has one level-1 index stronger or weaker. Among the six types, Type 1 (relatively strong Localization) has the highest number of countries (N = 52), Type 3 (relative strong Collaboration) is the second (N = 37), and Type 6 (relative weak Collaboration) has the lowest (N = 9). 5 representative countries from each cluster are drawn in the radar chats. The cluster results can give a rough but direct profile for each country and easily to know its relative strong/weak level-1 index helping the police makers to make decision when there is the need to improve ICE level.

Table 4
ICE Top 3 Countries from Different Continents (and their Global ICE Ranking).

	Africa	America	Asia	Europe	Oceania
Rank 1	Egypt (15)	United States (1)	Thailand (3)	United Kingdom (2)	Australia (4)
Rank 2	Cameroon (30)	Canada (9)	South Korea (7)	Russia (5)	New Zealand (14)
Rank 3	Madagascar (31)	Brazil (27)	Japan (10)	Germany (6)	Fiji (99)

Table 5
List of top 20 countries for ICE index obtained by CVM.

CVM Rank	Country	Localization Rank	Specialization Rank	Collaboration Rank
1	United States	5	1	1
2	United Kingdom	4	2	3
3	Thailand	11	5	4
4	Australia	2	3	8
5	Russia	8	7	5
6	Germany	1	12	9
7	South Korea	20	8	2
8	France	3	18	6
9	Canada	14	4	17
10	Japan	23	9	10
11	Italy	43	11	7
12	Spain	76	13	11
13	Indonesia	16	19	13
14	New Zealand	13	6	32
15	Egypt	73	14	14
16	Mongolia	25	25	12
17	Malaysia	21	10	33
18	Portugal	6	33	15
19	Laos	38	20	20
20	Cambodia	72	27	16

It is worth noting that even though type 1 is the largest cluster, there is no top ranked countries (the larger the area of triangle the better ranking). Although Type 4–6 is relatively weak in one dimension, in turn, for a country, it means that it performs better in the other two. As the smallest cluster, type 6 shows relatively weak Collaboration countries. There is no reliable evidence that there is a specific sequence of Specialization, Localization, and Collaboration development in all countries. However, the reason why Type 6 is rare may be that the early development stage of Chinese language education in various countries is mainly collaborative, and China provides some support for them. Then Specialization and Localization is easier to achieve. It is understandable that Collaboration in most countries is not so weak.

5. ICE ranking and the related potential factors

To explain the difference among three level 1 indexes and illustrate what and to what extent the external potential factors they are correlated with, a correlation analysis has been applied. Intuitively, we list several potential external factors that may be correlated to the level of ICE in the correlation analysis. There are 5 main parts in the external dataset, namely Economic Ties, Geographical Distance, Cultural Ties, and Government Polices, and China's Image.

- Economic Ties play a key role in language education. As the largest merchandise trade export country, China is the leading trade partners of more than 120 countries and regions. Close economical communication creates strong need of employees with Chinese language skills. As a "linguistic capital", the instrumental value of Chinese has become the main motivation and belief for students to learn (Wen Xu, 2023). As a result, the Chinese language education level can be driven by benefit. In our research, Trade Volume, Foreign Direct Investment (FDI) inflow and outflow volumes are selected as the proxy of Economic Ties. The Trade Volume with China can be found in China Statistical Yearbook yearly. However, the COVID-19 pandemic impacted international trade a lot in recent years, especially when countries were applying the lockdown policy. To decline the impact of pandemic and its consequences, the trade

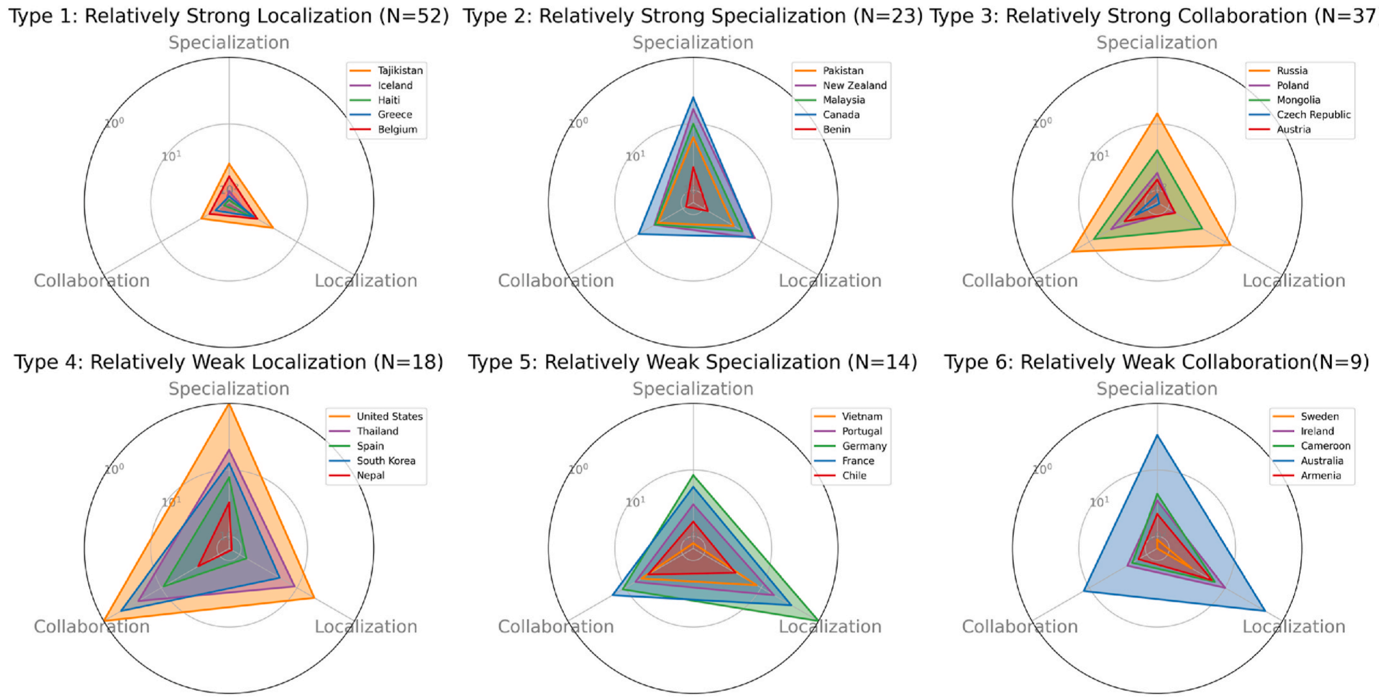

Fig. 2. Clustering result for the three dimensions of ICE ranking.

volume in 2019 was used as proxy. Similarly, every year Organization for Economic Co-operation and Development (OECD) will provide yearly FDI volumes between members and partners. We download the FDI inflow and outflow data regarding China.

- Geographical Distance between two countries is the most intuitive factor leading to the education of the language of each other. In this paper we collect the geographical distance data from French Center for International Economic Research (Centre d'Etudes Prospectives et d'Informations Internationales, CEPII). Geographical distance is determined with the distance between capital cities by CEPII. In addition, non-government people exchange like Number of Tourists is also highly correlated to geographical distance since 8 out of 10 China's main international tourist source markets are the neighboring countries of China (the else two are U.S. in 6th, and Singapore in 10th) in 2019 according to Ministry of Commerce of China.
- Another most intuitive factor could be Cultural Ties. Two countries with similar cultural ties may be more likely to prioritize the education of the other one's language. As for the cultural ties, we use the concept of cultural distance proposed by Geert Hofstede [41]. Cultural distance is described in six dimensions namely Individualism, Power Distance, Masculinity, Uncertainty Avoidance, Long-term orientation, and Indulgence. Each dimension represents a preference of country and is expressed on a scale from approximately 0 to 100.
- Besides, Government Policies can be another potential factor. However, collecting the quantified data to evaluate the policy is hard and the policy changed rapidly. As a compromise, we use some indirect proxies such as business volume of engineering project (Eng - Business Volume) and cooperative people exchange (Eng-Worker, Coop-Worker). The data is from the China Statistical Yearbook [42] too. What is more, the government efficiency and expenditure of education can have significant influence in country's Chinese language education level by ensuring policies efficiency, adequate funding, better infrastructure etc. And this part of data is from World Bank [43].
- People's evaluation of China's image from different countries is sociocultural factor. To explore the relationship between it and their ICE ranking, we used the Global Survey Report on China's National Image 2019 [44].

After the additional dataset is collected, a correlation analysis between three level-1 indexes and additional dataset is applied. The spearman correlation coefficient with significant level matrix is shown in Fig. 3. It shows that all the indicators have highly significant positive correlations with the economic ties such as FDI, Export and Import. But the correlation coefficients of each level-1 index are different, Localization has the highest correlation coefficient in FDI while for Collaboration is the Import and Export, and Specialization is in the middle position neither high nor low.

Another significant positive factor to all indicators is the number of outbound tourists to China. By contrast, the education expenditure does not show significant high correlation coefficient. Geographical Distance is negatively correlated to Localization and Collaboration but has no significant influence on Specialization while Government Effectiveness exactly shows different trends which is positive correlated to Localization and Collaboration. Surprisingly, Cultural Distances has not significant influence on any of three indexes.

Localization and Collaboration are correlated to Government Effectiveness; and only Specialization is significant correlated to China's Image Score. It is worth noting that perhaps the relationship between some factors like China's Image Score and the development level of ICE development is not directly generated, but the result of the intermediate role of other two reasons. Firstly, political, and diplomatic factors play a key role. For instance, BRICS countries (Brazil, Russia, India, China, and South Africa) have a high evaluation of China's image. Secondly, economic influence is becoming stronger, and countries which are great beneficiaries of China's economic and trade activities, tends to have a high evaluation of China's image [44]. Moreover, each level-1 index has its own special external factors which have significant correlation relationship, indicating our level-1 indexes are independent to some extent and making the ranking result explainable and reliable.

These findings may suggest that Chinese language education is mainly driven by trade and non-governmental exchanges, rather than official communications. It is unsurprising that geographical distance and cultural distance have a negative correlation with Collaboration. In

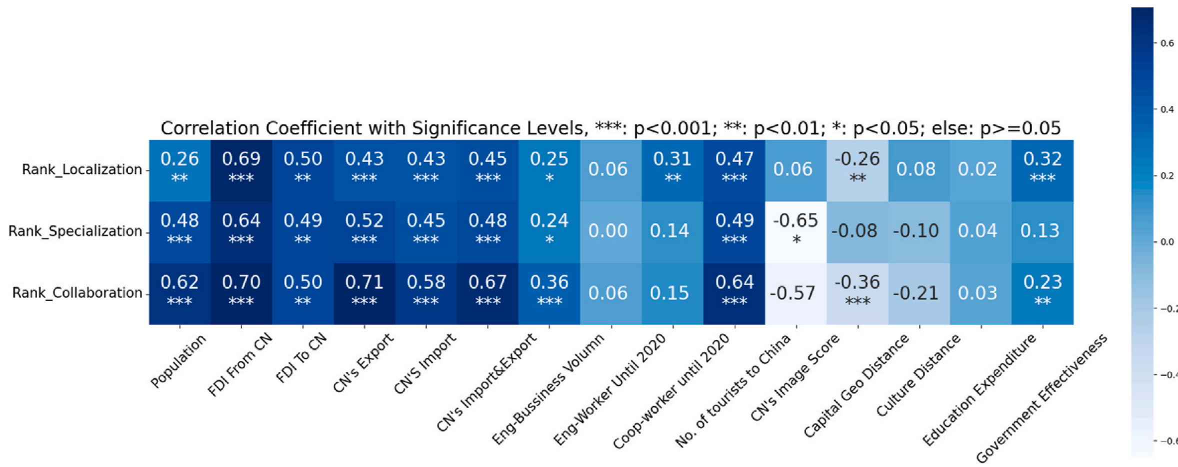

Fig. 3. Correlation of Three Dimensions of Ranking vs. Various Factors.

addition, each dimension is accompanied by a variable that is significantly correlated with it, indicating that the design of our evaluation system's three dimensions is reasonably distinct and non-overlapping.

These findings also provide practical inspiration for promoting the development of ICE in some countries. For instance, we should attach great importance and attention to some countries, like Mexico, Chile, and Argentina with great potential for development, which are relatively backward in the development of ICE, but have a good impression of China [44]. More importantly, on one hand, China should continue to strengthen its economic and trade relations with these countries to help improve their national economies and further expand the demand for ICE. On the other hand, China should provide more resources and pay more attention to helping these countries vigorously develop ICE, which will contribute to their rapid development in a two-pronged way.

6. Conclusions and further discussions

This paper proposed a comprehensive ICE ranking system with clearly defined 3-level indicators and attempts the combination of four weighting methods with PEM to build the rankings in ICE. Result shows CVM is the most representative method and according to the ranking result we detected 6 different types of countries by K-Means algorithm. Besides, we applied a correlation analysis with external dataset to explain the results to ensure the reliability of the rankings. Results show that the U.S., U.K., and Thailand rank in the top three in ICE index, followed by Australia, Russia, Germany, South Korea, France, Canada, and Japan are also in the top ten rankings.

We further find through correlation analysis that the level of ICE development is significantly positive correlated with its economical communication, and number of tourists, and negatively correlated to the geographical and cultural distance to China. Localization and Specialization has its own special external factors which have significant correlation relationship while Collaboration does not, indicating our level-1 indexes are independent to some extent and making the ranking result explainable and reliable.

Given that Hong Kong, Macau, and Taiwan invest much less in ICE than mainland China, even most of the data we collected focuses on the situation related to mainland China, it should also reflect the overall development and promotion of ICE in the whole Greater China region.

We also pay attention to the relationship between data completeness and ICE ranking of different countries. In general, there is a positive relationship between the data completeness of most countries and their ICE ranking, i.e., the better the ICE ranking, the higher the data completeness and vice versa.

However, there are some special cases. For instance, although Bosnia and Herzegovina (76.92 %), Belgium (76.92 %), and the Czech Republic (71.79 %) have higher data completeness, their ICE ranking is relatively backward, mainly due to inferior performance in Collaboration. There is much room for improvement in indicators such as the number of ICE teachers sent from China, teachers sent to China for training, and learners enrolled in Confucius Institutes. Conversely, countries such as Morocco (38.46 %), Mexico (38.46 %), Serbia (38.46 %), and Tanzania (38.46 %) have lower data completeness, but their relatively high rankings are due to outstanding performance in Collaboration. In addition, Mexico, Serbia, and Tanzania excel in indicators such as guarantee and system under Localization, reflecting a higher level of ICE and greater potential for development.

Future work includes correlation analysis with data on media attention on ICE topics, experimenting with other weight methods and ranking methods, and supplementing less complete data to provide support for improving the database related to the development of ICE.

CRediT authorship contribution statement

Hui Chen: Conceptualization, Methodology, Validation, Project administration, Investigation, Funding acquisition, Supervision, Writing - Original Draft, Writing - Review & Editing. **Zhengze Li:** Methodology, Software, Data curation, Visualization, Writing - Original Draft, Writing - Review & Editing. **Xue Wang:** Investigation, Data curation, Software, Validation, Writing - original draft, Writing - Review & Editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Hui Chen reports financial support and administrative support were provided by Beijing Foreign Studies University and Centre for Language Education and Cooperation. Zhengze Li reports administrative support and statistical analysis were provided by Sino-German Institute of Social Computing.

Data availability

Data will be made available on request.

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