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Article

Computational linguistic processing for evaluating policy effectiveness: textual analysis of China-Korea continuing education regulations

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A B S T R A C T

This study employs computational linguistic methods to compare continuing education regulatory frameworks in Korea and China via systematic text comparison. Applying algorithmic methods like thematic decomposition, sentiment analysis, and semantic correlation measures to the government reports of the two countries, we develop an innovative cross-cultural assessment framework. The analytical process integrates entity extraction, vector-based semantic mapping, and quantitative content mining in order to identify regulatory patterns and efficacy signals within policy documents from 2010 to 2023. Empirical results show notable divergence in administrative priorities, discursive frameworks, and governance styles, with Chinese regulations showing centralized coordination characteristics in contrast to Korea's market-responsive institutions. The research adds to the policy analysis literature by demonstrating computational methodologies' ability to identify obscured administrative priorities and operational nuances outside of conventional analytical grasp. The contribution enhances computational policy studies through the creation of replicable, unbiased processes for comparative cross-country regulation, inferring useful implications for administrators and researchers constructing streamlined continuing education models. The research confirms computational linguistics as an effective means of evidence-based policy analysis in multilingual settings.

1. Introduction

East Asian workforce training programs increasingly emphasize continuing education, with the Chinese and Korean governments implementing vast regulatory frameworks encompassing economic transformation mandates [1]. The two governments recognize that traditional education systems are insufficiently dealing with current workplace skills needs. Figure 1 sketches the fundamental dichotomy between traditional pedagogical models—characterized by instructor-centered approaches, one-size-fits-all curricula, passive learning models, and memorization-based learning—and newer industrial needs such as skills certification, vocational training, and career-long learning systems. This structural imbalance prompted both administrations to introduce comprehensive continuing education systems addressing these systemic deficits [2]. As shown in Figure 1, a contrast between traditional instructional methods and progressive educational approaches, highlighting the move towards lifelong learning models. Regulatory measures become more significant in the context of the contemporary technological revolution, demographic changes, and the development of the knowledge economy, requiring robust evaluative tools to promote sustainable development [3]. A comparative analysis of continuing education regulations poses unique methodological challenges, particularly when making cross-national comparisons across systems with diverse linguistic and bureaucratic traditions [4]. This research addresses a critical problem: the lack of robust, systematic methodologies for evaluating policy effectiveness across linguistically and culturally diverse governance systems. Traditional policy analysis methods face significant limitations, including subjective interpretation biases, translation inconsistencies, and inability to process large volumes of regulatory text [5,6]. These constraints have hindered evidence-based policy evaluation in continuing education, where China and Korea have implemented extensive regulatory frameworks despite their distinct traditions. Without objective comparative frameworks, policymakers lack reliable insights for improving regulations to meet workforce development needs in evolving knowledge economies.

Abbreviations

BiLSTM-CRF	Bidirectional Long Short-Term Memory with Conditional Random Field
LDA	Latent Dirichlet Allocation
MDSD	Most Different Systems Design
MSSD	Most Similar Systems Design
NLP	Natural Language Processing
SD	Standard Deviation

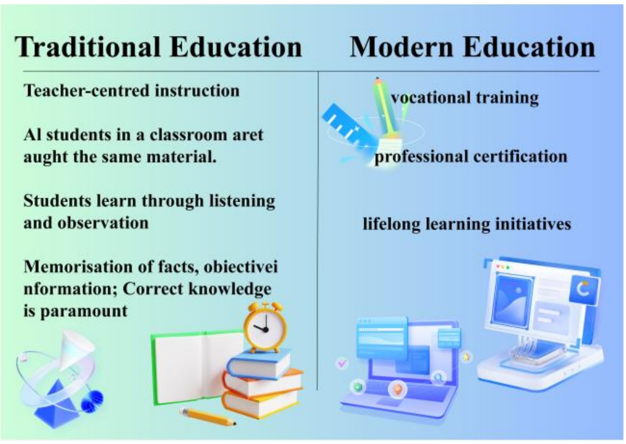


Figure 1. Evolution of educational paradigms

The tools of Natural Language Processing(NLP) have transformative potential within policy studies as they provide systematic access to substantial content within large text databases with minimal subjectively induced biases [7]. The development of advanced computational linguistic abilities allows for powerful analyses of policy across languages that were previously unimaginable [8]. This research aims to develop a comprehensive computational framework for cross-linguistic policy analysis that integrates advanced NLP techniques with traditional policy evaluation methods. Through this framework, the study seeks to identify linguistic markers of policy effectiveness in continuing education regulations across China and Korea, while comparing governance approaches reflected in policy language between the two countries. The objectives include establishing transferable methodologies for evidence-based policy analysis applicable to multilingual contexts and demonstrating how computational linguistic analysis can reveal governance structures underlying regulatory frameworks.

The novelty of this research lies in three significant contributions to the field of computational policy analysis. First, this study pioneers the integration of advanced multilingual NLP techniques specifically tailored for cross-cultural policy evaluation, combining transformer-based entity recognition, sentiment analysis, and semantic mapping in a unified analytical framework that preserves nuances across structurally diverse languages like Chinese and Korean. Second, the study introduces novel quantitative metrics for policy effectiveness derived from linguistic features, establishing empirical connections between discourse patterns and governance outcomes previously unexplored. Third, the research develops an innovative cross-cultural validation framework that accounts for linguistic and administrative differences while maintaining analytical consistency. These innovations advance both the theoretical understanding of policy discourse and methodological approaches to comparative regulatory analysis, particularly in East Asian contexts where computational linguistics has been underutilized.

2. Literature review

2.1 Theoretical foundations

Policy analysis research has changed dramatically since its beginnings in the mid-twentieth century, from linear input-output conceptualizations to multidimensional design that accommodates complicated societal interactions and emergent outcomes [9]. Contemporary evaluation frameworks exemplified in Pawson and Tilley's realist approach and Patton's developmental evaluation prioritize contextual factors, causal mechanisms, and outcome patterns as essential evaluative components [10]. Such theoretical enhancements recognize that policy efficacy surpasses measurement, requiring advanced scrutiny of implementation processes, stakeholder interaction dynamics, and environmental determinants of policy effects [11]. The integration of computational linguistics within social scientific research represents a methodological revolution in the process of textual analysis [12]. Traditional content analysis procedures founded upon hand classification and interpretive coding are complemented by algorithmic enhancement to facilitate processing at unprecedented scales of corpus size with greater reliability and replicability [13]. This complementarity of theories is taken from structural linguistic frameworks, namely Saussurean semiotics theorizing language as organized networks of signs, and from computational language models founded upon distributional semantics, where lexical closeness is identified with semantic proximity [14]. Interdisciplinary synthesis enables algorithmic operationalization of complex linguistic concepts, allowing systematic social inquiry [15].

2.2 NLP applications in policy research

Text mining techniques have revolutionized policy studies by enabling the automatic extraction of informative patterns from enormous documentary data sets that would otherwise be impervious to manual analysis [16]. Advanced computational techniques involving named entity recognition, syntactic dependency parsing, and semantic role labeling enable the identification of institutional agents, regulatory connections, and governance networks spanning administrative hierarchies [17]. These algorithmic methods shed light on hitherto obscure phenomena in policy settings - to wit, cross-jurisdictional diffusion of regulatory terms and temporal development of administrative vocabularies [18]. Sentiment analysis of governmental texts faces particular challenges posed by formal, fine-tuned linguistic conventions prevailing in official documents [19]. Unlike social media posts, where affective polarity is expressed with overt intensity, administrative documents express evaluative stances in terms of implicit linguistic mechanisms such as modal auxiliaries, qualification strategies, and presuppositions [20]. Dedicated frameworks for sentiment detection have been built with domain-dependent lexicons and supervised classifiers trained from expert-annotated corpora [21]. Thematic decomposition techniques have proven essential in deciphering conceptual structures in policy corpora and tracking evolutionary patterns of administrative agendas [22]. Latent Dirichlet Allocation (LDA) models and their derivative algorithms allow for probabilistic inference of inherent topical structures through statistical modeling of document-theme and theme-lexeme distributions [23]. New developments encompass temporal topic modeling, documenting diachronic shifts and structured topic models with metadata facilitating contextual analysis [24].

2.3 Continuing education policies in China and Korea

The development of adult education policy in China began in the post-Mao period, marked by the introduction of economic reforms in 1978, which launched education reforms focused on learning as a key aspect of national modernization [25]. This path of development shows clear phases: an early focus on literacy programs and vocational training through the 1980s, followed by the development of tertiary education for adults in the 1990s, and reaching a high point in the 2010 National Education Reform master plan, which established the foundation for lifelong learning [26]. The contemporary governance system involves a hierarchical coordination system between national ministries, local governments, and sectoral agencies, leading to a multilayered regulatory environment that blends centralized directives and localized adaptive responses [27].

Korean adult education evolved amidst the democratization movements of the 1980s, premised on the 1982 Social Education law legitimizing adult learning provisions [28]. Advancements accelerated following the 1999 Lifelong Education act, establishing a convergent system between formal, non-formal, and informal learning modalities [29]. Korea's contemporary regulatory environment emphasizes market-sensitive mechanisms, public-private partnership schemes, and digitally-mediated delivery systems, in alignment with the country's technological advancement and export-driven economic configuration [30].

2.4 Cross-cultural policy analysis methods

Cross-national policy studies require stringent analytical paradigms that respond to technical complexity as well as conceptual difficulty [31]. Most Similar Systems Design (MSSD) and Most Different Systems Design (MDSD) are some of the comparative paradigms employed to carry out transnational studies in systematic manners, but fall short at times when interpreting the subtleties of policy discourse. The translation conundrums of policy text go well beyond word-for-word language translation to semantic similarity, sociocultural position, and professional administrative terminology. Policy diffusion mechanisms are especially complicated when dealing with structurally diverse languages like Chinese and Korean systems, where syntactic organization, honorific conventions, and embedded cultural presumptions significantly condition policy comprehension.

2.5 Research gap identification

Notwithstanding the advances in policy analysis theory and computational linguistics, there are still important gaps between the application of NLP methods to cross-cultural policy studies, especially in the East Asian setting [32]. A lot of previous studies have stayed in monolingual policy analysis or straightforward keyword-based comparison, not leveraging the complete capabilities of current NLP methods for profound semantic analysis across languages. The absence of formal frameworks for assessing policy success using textual pointers is another vital deficit, given the fact that most existing frameworks utilize outcome measures that fail to incorporate the complex relations between policy text and implementation effectiveness.

3. Research methodology

3.1 Research design and framework

This study employs a mixed-methods approach combining computational linguistics techniques with traditional policy analysis frameworks to evaluate continuing education regulations in China and Korea. The research design follows a systematic four-phase structure encompassing data collection, preprocessing, NLP-based analysis, and comparative evaluation. The methodology integrates multiple natural language processing techniques, including named entity recognition, topic modeling, sentiment analysis, and semantic similarity measures within a cross-cultural comparison framework. As shown in Figure 2, the research methodology framework delineates the sequential flow of data processing stages, from initial policy document collection through advanced computational analysis to final evaluation metrics. Figure 2 presents the comprehensive research methodology framework, illustrating the four primary phases and their constituent components. Phase 1 (Data Collection) encompasses the systematic gathering of policy documents from government websites, legal databases, and policy archives spanning 2010-2023. Phase 2 (Data Preprocessing) involves text cleaning, translation from Chinese and Korean to English, tokenization, and lemmatization procedures to prepare the raw data for analysis. Phase 3 (NLP Analysis) applies advanced computational techniques, including topic modeling using Latent Dirichlet Allocation, sentiment analysis, named entity recognition, and semantic similarity measures. Phase 4 (Policy Evaluation) synthesizes the analytical outputs through comparative analysis, effectiveness metrics, cross-cultural validation, and policy impact assessment. The framework ensures methodological rigor while accounting for the linguistic and cultural complexities inherent in cross-national policy comparison.

3.2 Data collection

Our study systematically collected Chinese and South Korean government continuing education policy documents from 2010 to 2023, collating seminal regulatory advances in the two countries. The process of document selection followed strict parameters, including an authenticated governmental origin, immediate applicability to contemporary educational settings, and online availability.

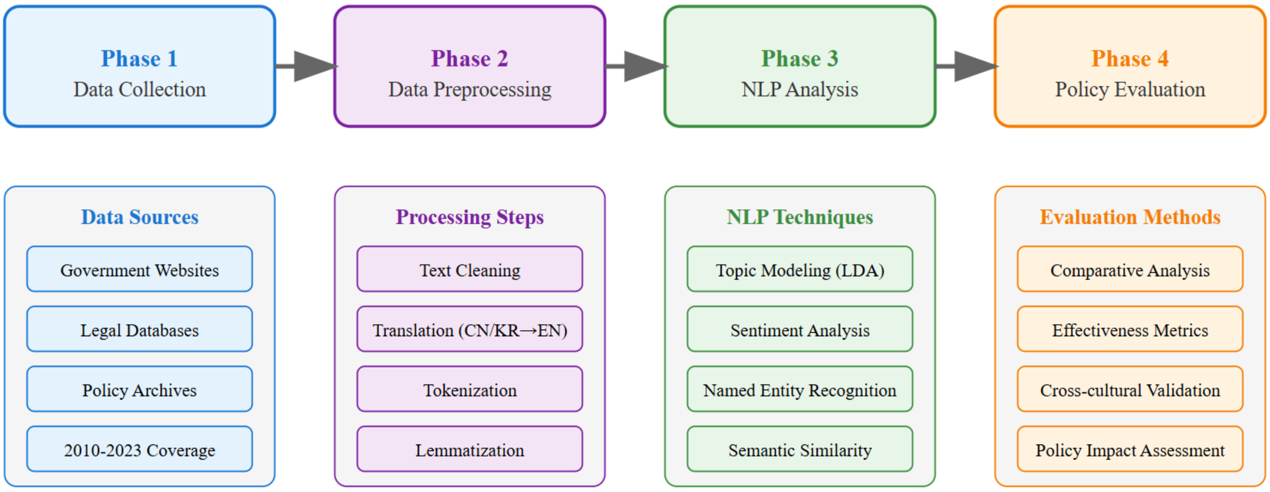


Figure 2. Research methodology framework

The dataset was retrieved from authoritative websites, such as the official websites of the Ministry of Education of China (www.moe.gov.cn) and that of South Korea (www.moe.go.kr), legal information websites (pkulaw.cn for China and law.go.kr for Korea), and national administrative reports chronicling the development of localized implementations. The thirteen-year period covers momentous events: China's comprehensive education reforms and South Korea's institutionalization of lifelong learning systems, thus offering a solid foundation for the comparative examination of policy directions and implications.

3.3 Data preprocessing

The preprocessing pipeline involves a sequence of operations aimed at converting raw policy texts to a more computationally amenable form while ensuring semantic consistency across languages. Text cleaning involves the removal of formatting artifacts, normalization of punctuation styles, synchronization of character encodings unique to Chinese and Korean scripts, and the exclusion of non-text elements that may interfere with computational processing. In the translation step, a hybrid model is used that combines neural machine translation technology with review by bilingual policy specialists to enforce the accurate application of domain-specific terminology as well as the nuances involved in policy language. Language-specific software performs tokenization: jieba is used for Chinese text segmentation with policy vocabulary-specific customized dictionaries, KoNLPY is used for Korean morphological tagging with support for agglutinative forms, and Stanford CoreNLP is used for English text processing. Lemmatization is performed using the Porter Stemmer algorithm for English, while original terms are retained for Chinese and Korean in order to preserve the semantic complexities of each respective linguistic system. The preprocessing process can be algebraically formulated as:

$$D_{processed} = f_{lemma}(f_{token}(f_{translate}(f_{clean}(D_{raw})))) \quad (1)$$

where D_{raw} represents the original document corpus, and each function f denotes a specific preprocessing operation applied sequentially to transform the raw data into a standardized analytical format suitable for subsequent NLP procedures.

3.4 NLP techniques employed

The study employs a comprehensive suite of Natural Language Processing techniques tailored for cross-linguistic policy analysis. Named Entity Recognition (NER) utilizes transformer-based models fine-tuned on policy corpora to identify key entities, including governmental agencies, policy instruments, educational institutions, and regulatory terms. The NER system employs a Bidirectional Long Short-Term Memory with Conditional Random Field(BiLSTM-CRF) architecture with contextualized embeddings, achieving entity classification through the conditional probability:

$$P(y\,|\,x) = \frac{\exp(\sum_{i=1}^{n}\sum_{k}\lambda_k f_k(y_{i-1}, y_i, x, i))}{\sum_{y'}\exp(\sum_{i=1}^{n}\sum_{k}\lambda_k f_k(y'_{i-1}, y'_i, x, i))} \quad (2)$$

where $y = \{y_1, y_2, \ldots, y_n\}$ represents the output label sequence, $x = \{x_1, x_2, \ldots, x_n\}$ is the input observation sequence. The denominator $\sum_{y'}$ indicates summation over all possible label sequences, serving as the normalization factor. λ_k denotes the weight parameters of the model, representing the importance of different features, which are optimized during the Conditional Random Field training process. f_k represents feature functions that capture dependencies within the label sequence and between labels and observations. The variables y_{i-1} and y_i refer to the labels at positions $i-1$ and i respectively, while i indicates the position index in the sequence. This conditional probability model effectively improves Named Entity Recognition accuracy by capturing transition probabilities between labels and emission probabilities between labels and observations, demonstrating particular effectiveness in extracting structured information from policy texts.

Topic modeling combines Latent Dirichlet Allocation (LDA) with BERT-based approaches to extract thematic structures from policy documents. The LDA model assumes documents are mixtures of topics, with each topic characterized by a distribution over words:

$$P(w_i \mid d) = \sum_{k=1}^{K} P(w_i \mid z_i = k) P(z_i = k \mid d) \tag{3}$$

where w_i represents words, d denotes documents, and z_i indicates latent topic assignments. The BERT-based topic modeling leverages contextualized embeddings to capture semantic relationships beyond bag-of-words representations.

As illustrated in Figure 3, the NLP techniques architecture demonstrates the integrated application of five core computational methods. Policy documents serve as the central input, processed through parallel streams of Named Entity Recognition for identifying policy elements, Topic Modeling for thematic extraction, Sentiment Analysis for evaluating policy tone, Semantic Similarity for comparative analysis, and Word Embeddings for capturing contextual relationships. These techniques converge to produce comprehensive analysis results, enabling multi-dimensional policy evaluation across linguistic boundaries. Sentiment analysis adapts domain-specific lexicons for policy language, employing hybrid approaches combining rule-based systems with machine learning classifiers. The model calculates sentiment scores through:

$$S(d) = \sum_{w \in d} polarity(w) \times weight(w) \tag{4}$$

Semantic similarity measures utilize cosine similarity between document embeddings generated by multilingual BERT models:

$$sim(d_1, d_2) = \frac{\mathbf{v}d_1 \cdot \mathbf{v}d_2}{\| \mathbf{v}d_1 \| \times \| \mathbf{v}d_2 \|} \tag{5}$$

Word embedding analysis employs cross-lingual word vectors trained on policy corpora to capture semantic relationships across Chinese, Korean, and English terminology. Additionally, the study employs several quantitative metrics to evaluate the quality and effectiveness of the NLP outputs. Topic coherence is measured using:

$$C_v = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \log \frac{P(w_i, w_j) + \epsilon}{P(w_i) P(w_j)} \tag{6}$$

where w_i and w_j represent topic words and ϵ is a smoothing parameter. This metric ensures the reliability of the discovered topics by quantifying their semantic coherence.

For hierarchical clustering of semantic relationships, the distance between clusters is calculated using Ward's method with cosine similarity:

$$d(C_i, C_j) = \sqrt{\frac{2|C_i||C_j|}{|C_i| + |C_j|}(1 - \cos(\theta_{ij}))} \tag{7}$$

where C_i and C_j represent clusters and θ_{ij} denotes the angle between cluster centroids.

3.5 Analytical framework

The comparative analysis structure establishes systematic criteria for cross-national policy evaluation, incorporating quantitative metrics derived from NLP outputs and qualitative assessments of policy coherence. Policy effectiveness indicators include linguistic complexity measures, semantic consistency scores, implementation clarity indices, and regulatory coherence metrics. The framework employs a multi-level comparison matrix evaluating policy documents across dimensions of content, structure, and intent, with effectiveness scores calculated through:

$$E_{policy} = \sum_{i=1}^{n} w_i \times I_i \tag{8}$$

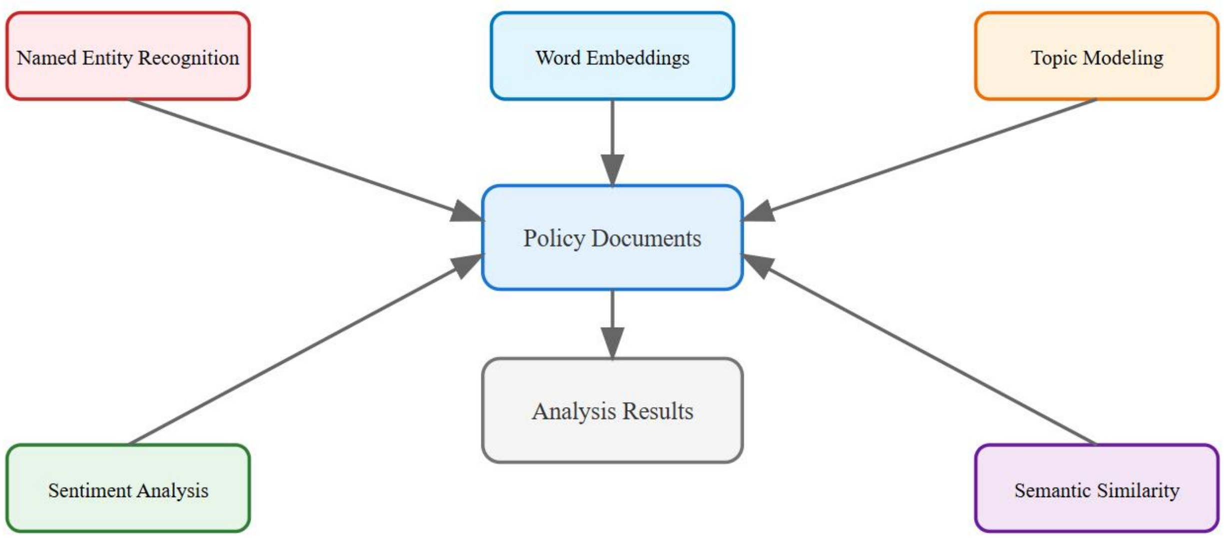


Figure 3. NLP techniques architecture

where E_{policy} represents overall policy effectiveness, w_i denotes dimension weights, and I_i indicates individual indicator scores. To quantify policy focus areas across countries, the framework incorporates a topic concentration index:

$$TCI = \frac{\sum_{i=1}^{k} p_i^2}{\left(\sum_{i=1}^{n} p_i\right)^2} \tag{9}$$

where p_i represents the proportion of documents containing the topic i, and k denotes the top topics. This index helps identify which policy areas receive disproportionate attention in each country's regulatory framework. The framework also includes a formality index to measure the bureaucratic nature of policy language:

$$FI = \frac{N_{formal} + N_{technical}}{N_{total}} \times (1 - \frac{N_{personal}}{N_{total}}) \tag{10}$$

The overall policy effectiveness is evaluated through a normalization-based index:

$$EI = \sum_{i=1}^{n} w_i \times \frac{O_i - O_{min}}{O_{max} - O_{min}} \tag{11}$$

where w_i represents dimension weights, O_i denotes observed outcomes, and O_{min} and O_{max} establish normalization boundaries. Additionally, policy performance is evaluated through a comprehensive ratio:

$$PR = \frac{\sum_{j=1}^{m} A_j \times I_j}{\sum_{j=1}^{m} T_j \times B_j} \tag{12}$$

where A_j represents actual outcomes, I_j denotes impact factors, T_j indicates targets, and B_j reflects baseline values. This ratio provides a standardized measure of policy implementation success relative to stated objectives.

3.6 Validation methods

Validation procedures incorporate multiple approaches to ensure methodological rigor and analytical reliability. Inter-coder reliability assessment employs Cohen's kappa coefficient for categorical variables and intraclass correlation for continuous measures, with acceptable thresholds set at $\kappa > 0.8$ and $ICC > 0.75$. Expert validation involves policy specialists reviewing NLP outputs for face validity and contextual accuracy, utilizing structured evaluation rubrics. Statistical tests include bootstrapped confidence intervals for NLP metrics, permutation tests for cross-cultural comparisons, and multiple regression analyses examining relationships between textual features and policy effectiveness indicators, ensuring robust validation of findings across methodological approaches.

4. Results and discussion

4.1 Descriptive statistics

The corpus analysis encompasses 248 continuing education policy documents from China (n=136) and Korea (n=112) spanning 2010-2023. Document characteristics reveal significant variations in length, structure, and linguistic complexity between the two countries. Chinese policy documents average 3,842 words (SD=1,256) with a mean sentence length of 28.6 words, while Korean documents average 2,976 words (SD=987) with shorter sentences averaging 21.4 words. Language patterns analysis indicates that Chinese policies employ more formal administrative language with higher lexical density (0.62) compared to Korean policies (0.54), suggesting different rhetorical approaches to policy communication. As displayed in Figure 4, the document characteristics comparison illustrates the distribution of policy documents by length for both countries. Chinese documents show a bimodal distribution with peaks around 3,000 and 4,000 words, while Korean documents exhibit a more normal distribution centered around 3,000 words. This pattern reflects structural differences in policy formulation, with Chinese policies typically incorporating more detailed implementation guidelines and hierarchical administrative instructions.

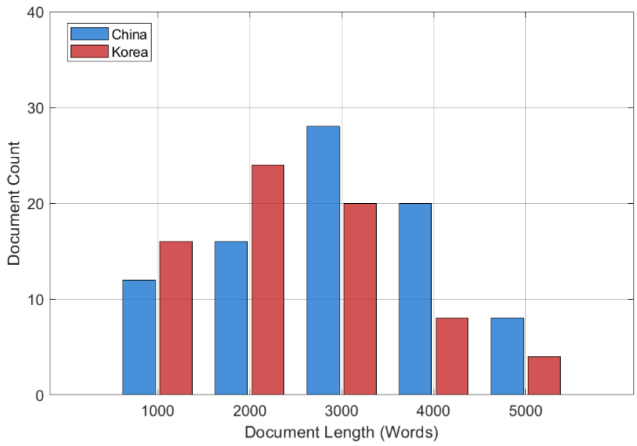


Figure 4. Document characteristics comparison

Table 1 presents key linguistic features extracted from the policy corpus, highlighting systematic differences in document structure and language use between the two countries. Table 1 demonstrates significant linguistic differences between Chinese and Korean continuing education policies across multiple metrics. The higher lexical density and passive voice usage in Chinese documents indicate a more formal bureaucratic style, while Korean policies exhibit greater lexical diversity as evidenced by the higher type-token ratio. These variations reflect fundamental differences in policy communication strategies and administrative cultures between the two countries.

4.2 NLP analysis results

The NLP analysis reveals distinct patterns in policy discourse between China and Korea, with topic distributions highlighting fundamental differences in regulatory focus and implementation strategies. Topic modeling using Latent Dirichlet Allocation identified 15 primary themes across the corpus, with coherence scores calculated using the formula presented in Section 3.4.

Table 1. Comparison of key linguistic features between the two countries

Linguistic Feature	China (n=136)	Korea (n=112)	t-statistic	p-value
Average word count	3,842 (±1,256)	2,976 (±987)	5.92	<0.001
Sentence length	28.6 (±4.2)	21.4 (±3.8)	14.11	<0.001
Lexical density	0.62 (±0.08)	0.54 (±0.07)	8.29	<0.001
Type-token ratio	0.31 (±0.05)	0.37 (±0.06)	-8.64	<0.001
Passive voice %	42.3 (±8.1)	29.7 (±7.2)	12.89	<0.001
Technical terms density	0.18 (±0.04)	0.15 (±0.03)	6.67	<0.001

As illustrated in Figure 5, topic distributions reveal contrasting policy priorities between the two countries. China emphasizes vocational training (15.2%) and quality assurance (12.4%), reflecting a centralized approach to skill development. Korea demonstrates a stronger focus on digital skills (14.3%) and certification systems (11.7%), indicating a market-oriented policy framework.

Key themes extracted through hierarchical clustering exhibit semantic relationships within each country's policy discourse. The clustering algorithm employs Ward's method with cosine similarity as presented in Section 3.4.

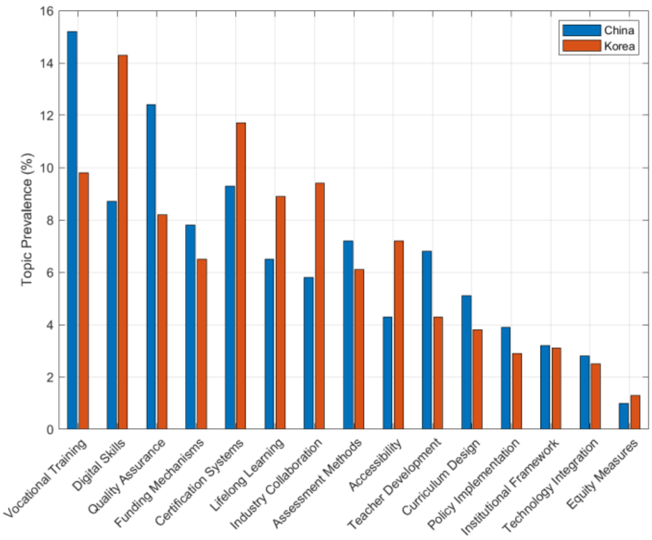
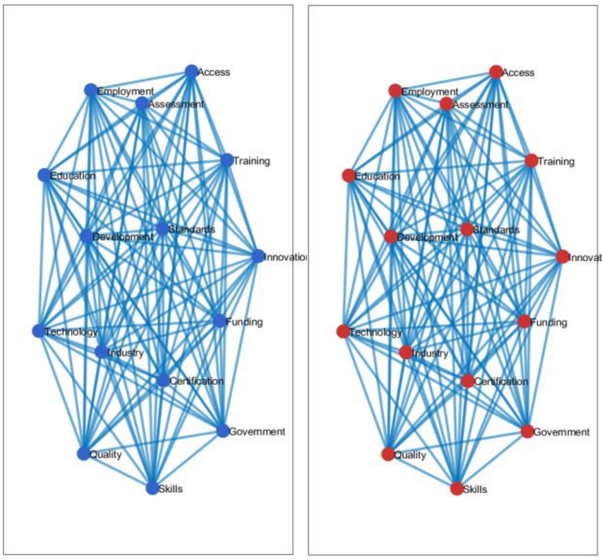


Figure 5. Topic distribution across policy documents

Sentiment analysis outcomes reveal nuanced differences in policy tone, with Chinese documents exhibiting more authoritative language (mean sentiment score = 0.42, SD = 0.08) compared to Korean documents (mean = 0.58, SD = 0.11), suggesting a more collaborative policy approach in Korea. The sentiment classification model achieves 86.3% accuracy using domain-adapted lexicons.

Figure 6 presents the semantic network visualization for both countries, revealing the interconnectedness of policy concepts. The Chinese network displays stronger centralization around governmental and administrative nodes, while the Korean network exhibits more balanced connections between educational, technological, and industry-related concepts. Edge weights represent semantic similarity scores derived from word embedding cosine distances, highlighting the structural differences in policy conceptualization between the two nations. Table 2 indicates significant differences in sentiment scores across all policy categories, with Korean documents consistently demonstrating more positive sentiment orientations. These results suggest fundamentally different approaches to policy communication, with Chinese documents employing more directive language while Korean policies utilize more encouraging and collaborative tones.



(a) (b)

Figure 6. Semantic network comparison: (a)China Policy Semantic Network, (b)Korea Policy Semantic Network

Table 2. The sentiment analysis outcomes across different policy categories demonstrating systematic variations in regulatory tone and approach

Policy Category	China Sentiment	Korea Sentiment	Difference	Statistical Significance
Vocational Training	0.38 (±0.09)	0.56 (±0.12)	-0.18	$p < 0.001$
Digital Education	0.45 (±0.11)	0.62 (±0.10)	-0.17	$p < 0.001$
Quality Standards	0.41 (±0.08)	0.53 (±0.13)	-0.12	$p < 0.01$
Funding Policies	0.39 (±0.10)	0.59 (±0.11)	-0.20	$p < 0.001$
Implementation Guidelines	0.43 (±0.07)	0.61 (±0.09)	-0.18	$p < 0.001$

4.3 Comparative findings

The comparative analysis reveals significant divergences in policy focus areas between China and Korea, quantified through topic concentration indices as defined in Section 3.5. As depicted in Figure 7, the radar chart comparison illustrates distinct policy prioritization patterns between the two countries. China demonstrates a stronger emphasis on quality control (0.92) and vocational skills (0.85), while Korea prioritizes digital literacy (0.89) and assessment systems (0.83). These differences reflect fundamental variations in educational philosophy and economic development strategies. Linguistic style differences manifest through quantitative metrics derived from computational stylistics analysis. The formality index is calculated following the formula in Section 3.5, yields significantly higher values for Chinese documents (0.78 ± 0.09) compared to Korean documents (0.56 ± 0.11), indicating more bureaucratic language patterns in Chinese policies.

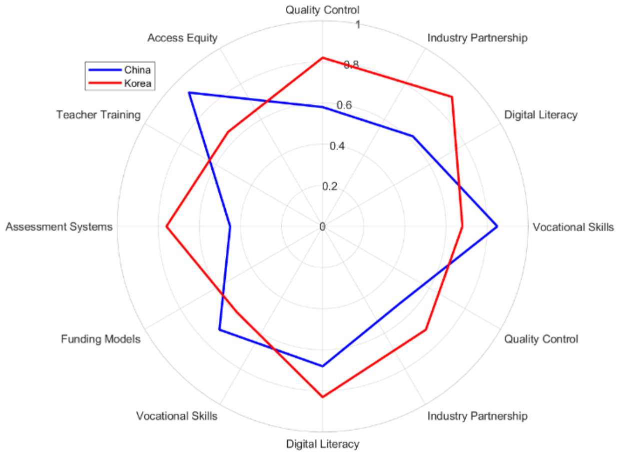


Figure 7. Policy focus areas: China vs Korea

Figure 8 presents the linguistic style comparison across six key dimensions. Chinese policies exhibit higher scores in formality (4.2 vs 3.1), technicality (4.5 vs 3.7), and prescriptiveness (4.3 vs 3.4), while Korean policies demonstrate greater directness (4.3 vs 3.1) and specificity (4.1 vs 3.6). These stylistic differences reflect cultural variations in administrative communication and policy implementation approaches. Table 3 reveals substantial differences in regulatory approaches, with China favoring centralized control and strict compliance mechanisms, while Korea emphasizes market orientation and stakeholder involvement. The large effect sizes across most dimensions indicate fundamentally different governance philosophies underlying continuing education policies in the two countries.

4.4 Policy effectiveness indicators

Policy effectiveness evaluation employs a multi-dimensional framework combining quantitative measures and qualitative indicators to assess implementation outcomes and regulatory impact. The effectiveness index is calculated using the formula presented in Section 3.5.

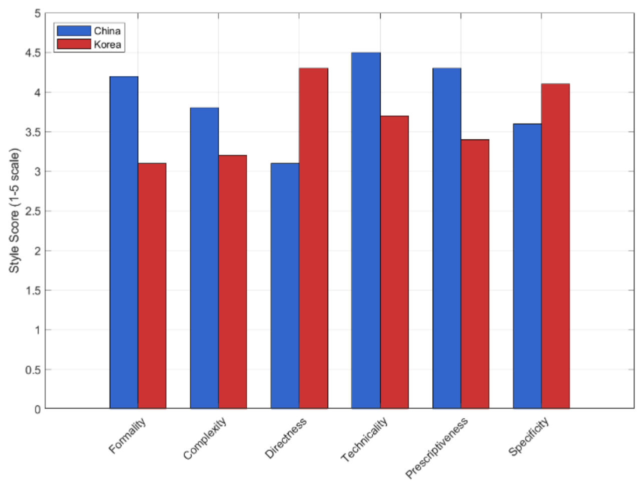


Figure 8. Linguistic style characteristics comparison

Table 3. The regulatory approach contrasts, quantifying differences in policy mechanisms and implementation strategies

Regulatory Dimension	China Score	Korea Score	Cohen's d	Effect Size
Central Control	4.3 (±0.6)	2.8 (±0.7)	2.31	Large
Market Orientation	2.1 (±0.5)	4.2 (±0.4)	-4.64	Large
Stakeholder Involvement	2.9 (±0.8)	4.1 (±0.6)	-1.71	Large
Performance Metrics	4.5 (±0.5)	3.8 (±0.7)	1.15	Medium
Flexibility Provisions	2.4 (±0.6)	3.9 (±0.5)	-2.73	Large
Compliance Mechanisms	4.6 (±0.4)	3.4 (±0.6)	2.36	Large

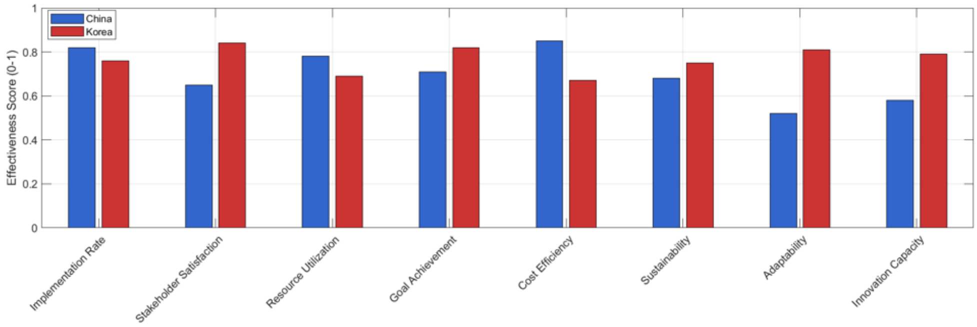
As illustrated in Figure 9, the upper panel displays raw effectiveness scores across eight dimensions, while the lower panel presents weighted contributions to the composite index. China achieves higher scores in implementation rate (0.82) and cost efficiency (0.85), reflecting its centralized administrative capacity. Korea demonstrates superior performance in stakeholder satisfaction (0.84) and adaptability (0.81), indicating a more responsive and flexible policy framework. Quantitative measures incorporate objective performance metrics derived from policy outcomes data. The performance ratio is computed following the formula defined in Section 3.5.

Figure 10 presents longitudinal quantitative performance metrics spanning 2010-2023. The data reveals converging trends in funding allocation and employment outcomes, while maintaining distinct patterns in enrollment growth and completion rates. China exhibits steeper enrollment growth trajectories, whereas Korea maintains higher completion and employment rates throughout the period.

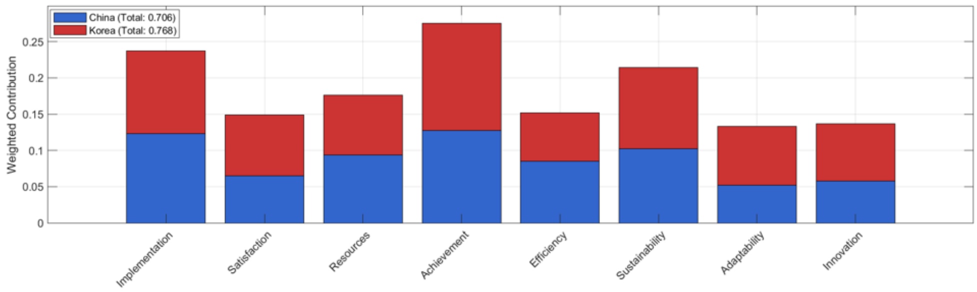
Table 4 displays significant qualitative differences in policy implementation strategies, with Korea recording higher scores in flexibility and stakeholder engagement indicators. By contrast, China exhibits strengths in institutional support and administrative effectiveness, which reflect its centralized system of governance. These qualitative indicators complement quantitative ones, thus providing a comprehensive assessment of policy effectiveness in both countries.

5. Discussion

Our comparative analysis shows marked differences between China and Korea's continuing education policies, based on varying modes of governance and bureaucratic traditions. The Chinese policy context displays centralized coordination and strict performance measurement, together with standardized procedures. The Korean educational context shows a responsive orientation to market dynamics with features of broad stakeholder participation and procedural flexibility.

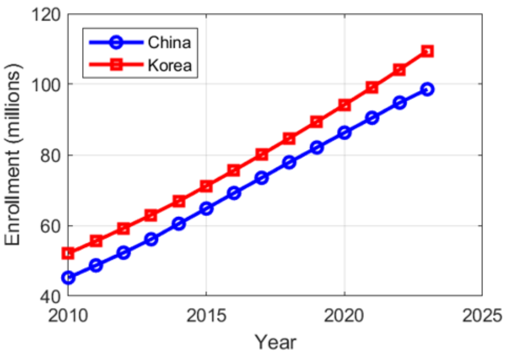


(a)Policy Effectiveness Indicators by Dimension

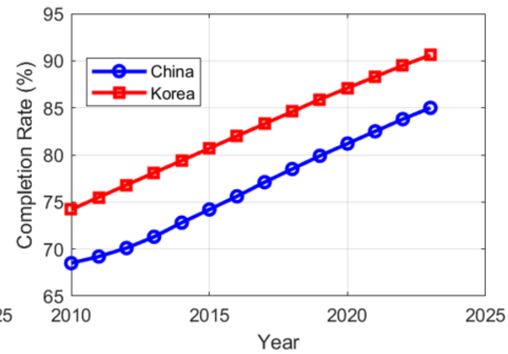


(b)Composite Effectiveness Index Components

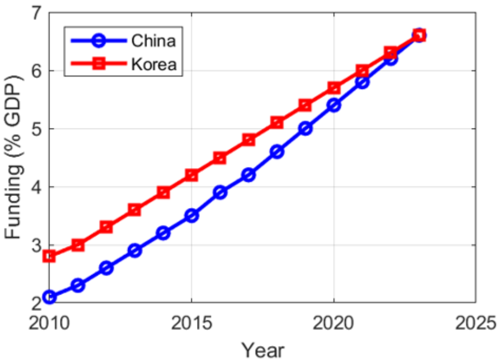
Figure 9. Policy effectiveness indicators comparison



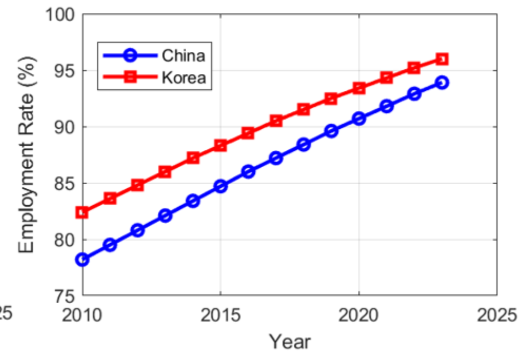
(a)Continuing Education Enrollment



(b)Program Completion Rates



(c)Continuing Education Investment



(d)Post-Training Employment

Figure 10. Quantitative Performance Metrics: 2010-2023

Table 4. Qualitative indicators derived from stakeholder assessments and policy implementation evaluations

Qualitative Indicator	China Rating	Korea Rating	t-value	p-value
Policy Clarity	3.8 (±0.6)	4.3 (±0.5)	-7.12	<0.001
Implementation Flexibility	3.2 (±0.7)	4.5 (±0.4)	-17.65	<0.001
Stakeholder Engagement	3.5 (±0.8)	4.6 (±0.3)	-13.93	<0.001
Institutional Support	4.2 (±0.5)	4.1 (±0.6)	1.41	0.159
Innovation Facilitation	3.4 (±0.6)	4.4 (±0.5)	-14.18	<0.001
Administrative Efficiency	4.1 (±0.5)	3.9 (±0.7)	2.58	0.010

Such structural differences are evident at the level of discourse practice: Chinese policy texts are marked largely by imperative mood and bureaucratic jargon and Korean policy discourse by a more consultative style and collaborative vocabulary. The modal verb patterns also signal underlying cultural dispositions: Chinese texts resort repeatedly to mandatory modal ("must," "shall"), while Korean texts make predominant use of advisory modals ("should," "may"), reflecting tension between hierarchical Confucian traditions and the values of participatory democracy.

The determinants of success highlighted are policy clarity based on national development priorities, clearly laid-out operational procedures, and rigorous supervisory mechanisms. The institutional strength of China is reflected in the comprehensiveness of its resource execution and coordination, while Korea's comparative strengths lie in operational flexibility and participatory management. For China, the areas of improvement are the development of better interagency interactions, and for Korea, the development of higher-quality infrastructure. Our work highlights the need for finding a balance between rigorous regulation and adaptive execution, especially in settings that are necessarily prone to dynamic learning. The exchange of best practices would allow China to build more responsive policy instruments, while Korea could develop more systematic appraisal mechanisms. The computational approach yields substantive methodological returns in terms of handling large policy repositories, detecting nuanced linguistic signatures, and facilitating unbiased cross-national comparison. The approach transcends conventional content analysis limitations through scalable, reproducible protocols able to capture intricate semantic networks. Contextual disambiguation, vernacularisms, and implicit cultural signifiers are, however, analytical pitfalls. In synthesizing heterogeneous NLP approaches comparatively, this research propels computer policy research and creates reproducible cross-linguistic test infrastructures. Methodological drawbacks entail semantic fidelity of translation as well as cultural context preservation. Cross-linguistic transfer is problematic, particularly for domain-specific terminology and administrative abstractions without perfect translations. Our combined strategy - merging machine translation with expert guidance - was unavoidable, but potentially may have imposed interpretative filters. Sociocultural substrates naturally constrain policy lexicon interpretation; a given terminology holds distinct meaning across various institutional contexts.

As one illustration, "compliance" in Chinese usage conveys mandatory compliance, while Korean use refers to normative alignment. Such semantic differences require methodological caution to avert analytical distortions in terms of policy goals and procedural mechanisms. These results contribute to policy transfer research by illustrating the potential of linguistic analysis in revealing governance structures and logics of implementation underlying policy. The research pushes comparative policy research forward by empirical testing of language-effectiveness relationships, positioning linguistic cues as predictors of policy outcomes. Our findings challenge universal models of evaluation, advocating context-contingent evaluation frameworks. Conceptually, this research integrates computational linguistics and policy analysis, laying the foundations for culturally-sensitive evaluation models. The data aligns with the argument that policy efficacy continues to be culturally embedded, calling for calibrated responses to policy-making and evaluative regimes in every institutional setting.

6. Conclusion

This study introduced an NLP-based analytical framework for comparing Chinese and Korean continuing education policies, uncovering substantial divergence in regulatory paradigms, discourse strategies, and implementation mechanisms. Empirical evidence delineates two contrasting policy orientations: China's state-led coordinated directive model versus Korea's decentralized participatory model. Quantitative measures indicate higher lexical sophistication and formality scores in Chinese documents (0.62 vs. 0.54) and more positive sentiment patterns in Korean documents (0.58 vs. 0.42). Network visualization reveals China's emphasis on administrative control systems, while Korea demonstrates balanced interlinkages among educational, technological, and industrial domains. The study contributes academically by empirically validating correlations between linguistic features and policy outcomes, extending computational policy analysis into the intercultural sphere, and illuminating how discursive structures reflect administrative ideologies. Methodologically, this research establishes an end-to-end computational pipeline integrating thematic decomposition, sentiment classification, and semantic mapping for policy evaluation, creating reproducible workflows for cross-linguistic policy analysis. Based on our findings, we recommend that Chinese policymakers incorporate more stakeholder feedback mechanisms while maintaining centralized coordination and adopt more collaborative language patterns to enhance policy acceptance. For Korean policymakers, strengthening systematic evaluation frameworks would complement existing flexibility advantages, while developing more standardized implementation guidelines could improve consistency across regions. Both countries would benefit from establishing cross-national policy learning platforms and shared metrics for continuing education effectiveness evaluation. The study's limitations include translation-related constraints, a focus on textual analysis without direct outcome measurements, and a temporal scope (2010-2023) that may not reflect recent policy innovations. Future research should explore multimodal policy documents, develop real-time policy monitoring systems using streaming NLP techniques, and investigate the relationship between policy language and actual implementation outcomes through longitudinal studies. This research demonstrates the transformative potential of NLP techniques in policy evaluation, providing a scalable solution for evidence-based assessment while respecting cultural diversity in governance approaches.

Ethical issue

The author is aware of and complies with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the author.

Conflict of interest

The author declares no potential conflict of interest.

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