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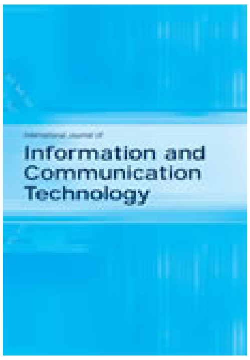

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English-derived place name recognition and translation based on knowledge graph and phonetic generation algorithm

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Abstract: This paper proposes a model for English-derived place name recognition and translation using a knowledge graph and a phonetic generation algorithm. By integrating multiple algorithms, the model enhances both recognition and translation accuracy. Experimental results show an AUC of 0.892. With 100 training iterations, the recognition error rate is 1.3%, the translation error rate is 0.8%, and the BLEU score reaches 67.3%, demonstrating strong performance. Practical analysis indicates the model has the lowest time consumption, minimal memory usage, superior classification performance, and over 95% fluency and consistency. The innovation of the research lies in the construction of a bidirectional dynamic interaction fusion mechanism through a knowledge graph, an LSTM algorithm, and a bidirectional matching maximum algorithm, targeting the semantic specificity of English-derived place names. This breaks the traditional one-way static fusion and achieves precise scene-based collaboration and closed-loop optimisation of semantics and phonetics.

Keywords: knowledge graph; phonetic generation algorithm; English-derived place names; recognition and translation; LSTM; bidirectional maximum matching algorithm.

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1 Background

English is one of the most widely used languages in the world and plays an important role in international politics, economy, culture, and technology exchanges (Chen et al., 2022). English recognition and translation offer substantial advantages to personal development, social communication, and industry applications (Zhong et al., 2023). In general, English recognition and translation refer to two core tasks that process words or sentences derived from etymology. These tasks restore the source and meaning of words and sentences accurately and ensure that users of the target language can understand and accept them (Mao et al., 2024; Wang et al., 2023; Prathwini et al., 2024). However, general translation work often suffers from inaccuracies, semantic drift, and difficulty handling large-scale data. To address these problems, scholars from various countries put forward a series of recognition and translation models. This system consists of three modules: speech recognition, text translation, and speech synthesis. Tests on datasets proved that the model achieved high translation quality (Zhu et al., 2024a). Experimental results showed that the model reduced error rates by 18% and 29% in both tasks, achieving better performance than a single model (Chen et al., 2024). Tayir et al. (2024) raised an encoder-decoder calibration method to improve multimodal machine translation quality. This method combines images and text and identifies key inputs in the decoder for translation. Experimental results showed that this method significantly improved the accuracy of English translation and achieved good performance (Yang et al., 2024a). Although current studies on English recognition and translation have improved performance in general scenarios, overcoming the bottleneck of domain adaptation and accurately processing specialised texts, such as English-derived place names and technical terms, remains a significant challenge.

Derived place names are new geographical terms generated by adding suffixes or semantic components to existing place names through linguistic processes. They are categorised into two types: entirely derived place names and generic derived place names. Fully derived place names consist entirely of the base name plus derived suffixes or semantic elements, retaining no original meaning. Generic derived place names combine the base name with standard geographical terms, preserving the core reference while adhering to standard naming conventions. The translation challenge lies in accurately reconstructing semantic relationships and spatial connections from the original name, adapting to target-language naming norms, and resolving mismatches between English directional terms and compound words. To achieve precise extraction, Hu et al. (2022) proposed an unannotated deep learning method using place names and synthetic data from microblogs. Experimental results showed an F1 score of 0.84. Berragan et al. (2023) developed a Transformer-based named entity recognition method for extracting place names from unstructured text, achieving an optimal F1 score of 0.939. Mamontova and Klyachko (2022) introduced a GIS-based community participation approach for indigenous dynamic place naming systems and local cartography. Experimental results demonstrate that this method has achieved remarkable success in indigenous toponymy and local cartography, effectively enhancing the accuracy and cultural sensitivity of toponymic naming. However, despite these advancements in toponymic research, challenges persist when dealing with the unique textual characteristics of English-derived toponyms. Consequently, there is an urgent need to develop more efficient and precise identification and translation methods tailored to the distinctiveness and complexity of such toponyms.

A knowledge graph combines theoretical methods of a discipline with bibliometric citation analysis, co-occurrence analysis, and other methods. It presents them as a semantic network in graph form (Hu et al., 2022; Berragan et al., 2023). A phonetic generation algorithm converts unstructured text into standardised phonetic symbols to link text with speech (Mamontova and Klyachko, 2022). Both the knowledge graph and the phonetic generation algorithm structure information, improving information comprehensibility and supporting intelligent processing. They lower the threshold of information use and have been widely applied in various fields (Zhu et al., 2022). Zhong et al. (2023) proposed a knowledge graph-enhanced network to understand long, complex sentences better and perform sentiment analysis. Tests on five popular benchmark datasets proved that the model achieved good performance, effectiveness, and robustness (Xie et al., 2022). Zhong et al. (2023) proposed a knowledge graph-based graph convolutional neural network fault diagnosis model to improve the accuracy of machine fault diagnosis. This model improved the rationality and diversity of fault tracing. Tests on two datasets confirmed its superior performance (Chaudhary et al., 2023). This method used phonetic generation to provide a basis for human speech decoding, significantly reducing labor costs. Experiments confirmed that this method had potential usefulness in computer-assisted translation (Dalva et al., 2023). In summary, the knowledge graph and the phonetic generation algorithm both demonstrate practical value that meets the requirements of related studies, and together they provide reliable technical support for intelligent information processing and applications across different fields.

The combination of a knowledge graph and phonetic generation algorithm enables efficient and accurate recognition and adaptive translation of English-derived place names through structured etymology, speech association information, and precise sound-shape mapping. Therefore, this paper proposes an English-derived place-name recognition and translation model based on a knowledge graph and a phonetic generation algorithm. This model is expected to break traditional bottlenecks, improve the accuracy of English-derived place name recognition and translation, and promote the field toward more intelligent development.

2 Methods

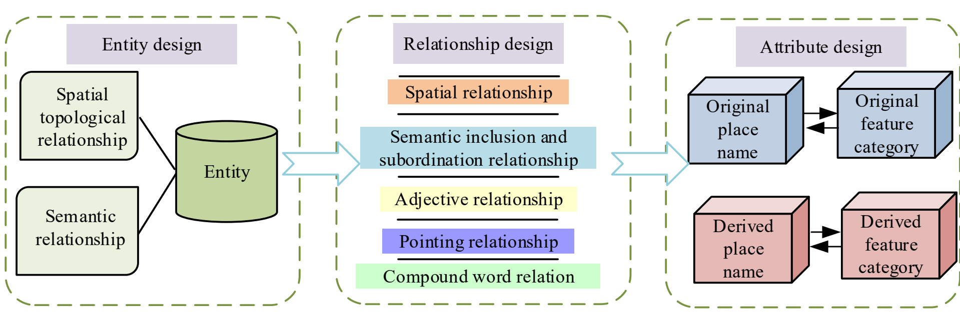
2.1 English-derived place name recognition model based on knowledge graph

The model uses a knowledge graph to extract semantic and derivation relationships of English-derived place names. This process reduces human resource costs and improves efficiency (Zhang et al., 2023a; Xi et al., 2024). The construction of the recognition model includes three steps: designing the knowledge graph, setting reasoning rules, and forming the quantitative expression of spatial constraints of the knowledge graph. First, the English-derived place name knowledge graph is designed. The basic process is shown in Figure 1.

As shown in Figure 1, the first step is entity design. Entities are defined and organised according to spatial, topological, and semantic relationships of derived place names. The primary data source for constructing the knowledge map is the US Geological Survey's Geographic Names Information System (GNIS). This database contains over 2 million geographical entity names and attribute information for the continental United States and its territories, providing authoritative and accurate data on place entities, types, and relationships to support research. This ensures the reliability and professionalism of the knowledge map construction. Additionally, the knowledge map incorporates supplementary information from authoritative dictionaries, academic literature, and online place name databases to enrich its semantic layers and coverage. The entity refers to the specific conceptual categories and instances of the corresponding spatial topological relationships and derived place name native place name semantic relationships covered by the map. The second step is to design relationships to clarify the association rules between entities when constructing a derived place name knowledge graph, including spatial relationships, semantic inclusion and subordination relationships, adjective relationships, and compound-word relationships. Spatial relationships refer to the association between derived land cover categories and native land cover categories at the spatial level. Semantic inclusion and subordination involve three entities: 'native place name common name', 'derived common name', and 'native land cover category', which form two layers of semantic association. The relationship between adjectives and native place names and derived place names is a semantic modification type of association. The directional relationship between 'native place name common name' and 'directional word derived common name' is a spatial reference type association. The relationship between compound words and 'native place name common names' and 'compound word derived common names' is a type of lexical combination association. The five types of relationships, with 'native entities' as the core, 'spatial associations' as the reality basis, 'semantic frameworks' as the rule core, and 'specific semantic derivation methods' as the landing means, jointly construct a complete association network of derived place names from geographic space to the semantic level. Next, reasoning rules are designed as shown in equation (1).

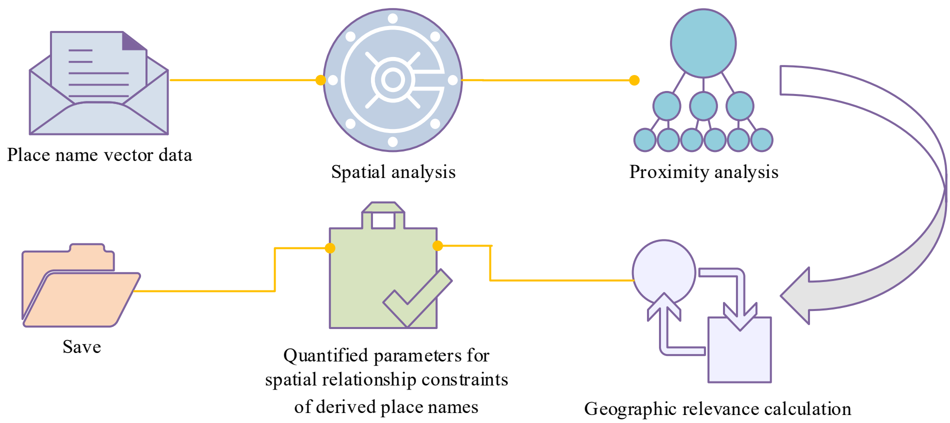
$$\begin{aligned}&(A \in C) \cap (B \in C) \cap (A, \textit{semantically contains}, a)\\&\cap (C, \textit{place name generic term}, a)\\&\cap (A, \textit{synonym}, B) \Rightarrow (B, \textit{semantically contains}, a)\end{aligned} \tag{1}$$

Figure 1 Knowledge graph structure of English-derived place names (see online version for colours)



In equation (1), A and B represent derived generic names, both belonging to the original place category C. a represents the generic name of the original place name C, *semantically* represents semantic inclusion, *place name generic name* represents generic place names, and *synonym* represents synonyms. This process is used to mine the implicit semantic relationships in the knowledge graph to construct a complete knowledge graph in the derivation domain. Then, the spatial constraints of the derived map knowledge graph are quantified. The technical route is shown in Figure 2.

Figure 2 Quantification process of constraints (see online version for colours)



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As shown in Figure 2, the technical route extracts place name information from related vector data, calculates the association between original and derived place names, and finally obtains the quantitative parameters of spatial relationship constraints of derived place names. In proximity analysis, proximity samples are collected first. The original place object layers with a separation relationship from the derived place objects are selected. The distance between derived place objects and the nearest original place objects is obtained by proximity analysis. A boxplot analysis is used, combined with the equation to calculate the normal distribution range of the sample data. Based on the statistical characteristics of the data, the paper assumes that the variables are normally distributed. After the distribution hypothesis is verified by the K-S test, the mean and variance of the distribution are estimated using maximum likelihood to quantify the probability characteristics of the spatial constraints. The upper and lower limits of the distribution interval are shown in equation (2).

$$\begin{Bmatrix} IQR = Q_3 - Q_1 \\ lower\_\lim it = Q_1 - 1.5IQR \\ upper\_\lim it = Q_3 + 1.5IQR \end{Bmatrix} \tag{2}$$

In equation (2), Q_3 and Q_1 represent the upper quartile and lower quartile, while *lower_limit* and *upper_limit* represent the cutoff points of outliers. Next, the proximity distance is estimated. The distance between derived place objects and original place objects is selected as a random variable. Its probability density function is calculated as shown in equation (3).

$$P(x) = \frac{x}{l}, \quad 0 \le x \le l \tag{3}$$

In equation (3), x represents the distance between original and derived place objects, and l represents the proximity distance. When $0 \leq x \leq 1$, it represents the probability density of the distance within this interval, and when $x < 1$, the density is 0. Based on this, the proximity distance is estimated using a distribution-point estimation equation. The calculation equation is shown in equation (4).

$$S = X_{(n)} + \frac{1}{n-1}\left(X_{(n)} - X_{(1)}\right) \tag{4}$$

In equation (4), n represents the total number of samples, $X_{(n)}$ and $X_{(1)}$ represent the maximum and minimum order statistics. Based on the proximity distance estimation, nearby original place objects are retrieved and place name information is obtained to complete the proximity analysis. Then, the degree of geographic association is calculated. To achieve practical calculation, the pointwise mutual information method is introduced to quantify the association strength between English-derived place names and corresponding geographic entities. However, this equation is not easy for computer operations, so it is optimised. The optimised equation is shown in equation (5).

$$PPMI(X, Y) = \log_2\left(1 + \frac{P(X, Y)}{P(X)P(Y)}\right) \tag{5}$$

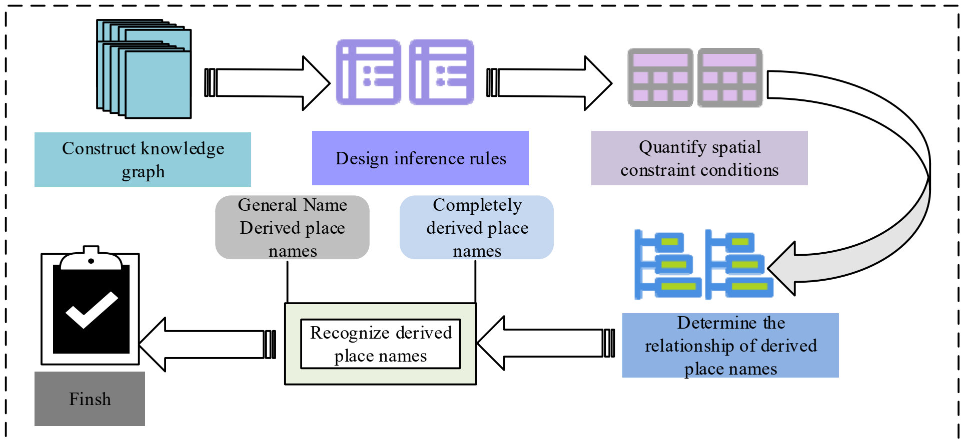
In equation (5), X and Y represent two discrete variables. The core of equation (5) is to add 1 to the denominator, which not only eliminates branch operations to adapt to massive geographic entity batch calculations, but also avoids calculation anomalies caused by extremely low joint probabilities. Finally, the calculation of the geographic association degree is shown in equation (6).

$$Correlation(D, S) = \log_2\left(1 + \frac{P(D, S)}{P(D)P(S)}\right) \tag{6}$$

In equation (6), D and S represent the place object categories of derived and original place names. According to the calculation result, the association degree between derived and original place objects can be determined. If the result is greater than 1, the association is strong. If it equals 1, there is no association. If it is within [0, 1], the association is weak. After completing the above steps, the model automatically recognises derived place names. It recognises both completely derived place names and generic derived place names based on the derivation judgment. The final knowledge graph-based English-derived place name recognition model is shown in Figure 3.

As shown in Figure 3, the model constructs a structured semantic network by building a knowledge graph. To address ambiguity in place name entity linking, it enhances entity matching accuracy by integrating geographical contextual features with historical toponym databases. The system then designs inference rules that specify the logical foundations for deriving relationships from the knowledge graph, ensuring rigorous, accurate reasoning. Spatial constraint quantification is implemented to measure geographical relationships, while embedded temporal stamps and administrative boundary adjustment records enable spatiotemporal evolution modelling. This approach visually reflects dynamic changes in place names, providing quantitative data support for subsequent identification. Building on this foundation, the model categorises derived place names into fully derived and generic-derived types for precise recognition and processing. Finally, the model outputs English-derived place name recognition results, concluding the entire workflow.

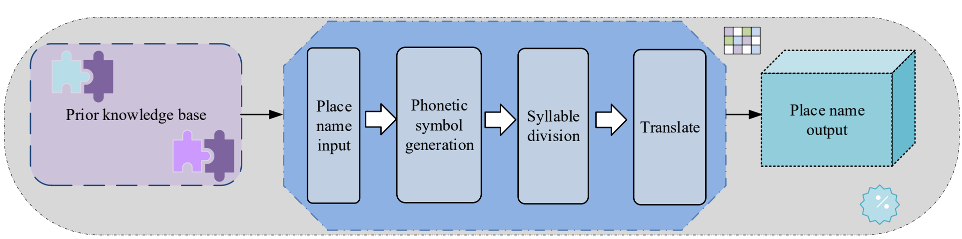
Figure 3 Derived place name recognition model operation process (see online version for colours)



2.2 *English-derived place name translation model based on phonetic generation algorithm*

The recognition of English-derived place names capture their etymological logic and cultural attributes, which lay a key foundation for accurate and culturally adapted translation. Translation plays a fundamental role in cross-language information transfer and supports global economic cooperation and cultural exchange (Li et al., 2023). Traditional machine translation often produces unclear recognition and irregular translation of place names. The phonetic generation algorithm analyses the pronunciation structures and phonetic-form associations of derived place names, providing support for standardised translation and addressing the challenges of machine translation (Yun et al., 2014). This study applies the phonetic generation algorithm to construct the translation model of English-derived place names. To improve translation efficiency, the model introduces a deep learning framework. The basic architecture is shown in Figure 4.

Figure 4 Schematic diagram of deep learning theoretical architecture (see online version for colours)



As shown in Figure 4, the architecture consists of two parts: building a prior knowledge base and phonetic translation of English-derived place names. The prior knowledge base includes an instance material library and a rule library. The phonetic translation starts by entering place names, then processes them, generates and optimises phonetics using the phonetic generation algorithm, segments syllables, and finally translates and outputs the translated names. However, this translation model struggles with the complex mapping between spelling and pronunciation and with long-distance dependencies in English-derived place names. The long short-term memory network (LSTM) captures these long-distance dependencies and complex contextual effects, improving phonetic recognition and translation efficiency (Rubasinghe et al., 2024). This study applies LSTM to phonetic recognition in the translation process to improve overall accuracy and efficiency. LSTM consists of three gates: the input gate, the forget gate, and the output gate. The forget gate filters redundant historical syllable information in the phonetic sequence of place names, preventing the accumulation of invalid information that interferes with the recognition of the current phonetic symbol. The calculation formula is shown in equation (7).

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, X_t\right] + b_f\right) \tag{7}$$

In equation (7), f_t represents the output of the forget gate, σ represents the activation function, W_t represents the weight matrix, h_{t-1} represents the output of the previous matrix, and b_f represents the bias. The input gate is responsible for writing the syllable features corresponding to the current place name text into the memory unit, accurately capturing the mapping relationship between text and phonetics. The calculation formula is shown in equation (8).

$$\left.\begin{cases} i_t = \sigma\left(W_i \cdot \left[h_{t-1}, X_t\right] + b_i\right) \\ c_t = \tanh\left(W_c \cdot \left[h_{t-1}, X_t\right] + b_c\right) \end{cases}\right\} \tag{8}$$

In equation (8), W_i and W_c represent the weight matrices of the input gate and the current unit. b_i and b_c represent the biases of the input gate and the current unit. The output gate outputs phonetic features adapted to the place name translation task based on the current memory state, and the calculation formula is shown in equation (9).

$$\left.\begin{cases} c_t = f_t \odot c_{t-1} + i_t \odot c_t \\ o_t = \sigma\left(W_o \cdot \left[h_{t-1}, X_t\right] + b_o\right) \\ h_t = o_t \odot \tanh\left(c_t\right) \end{cases}\right\} \tag{9}$$

In equation (9), W_o and b_o represent the weight matrix and bias of the output gate. After processing data through the input gate, forget gate, and output gate, the model captures the relationship between character sequences and phonetic sequences. The LSTM algorithm is combined with the phonetic generation algorithm to create the LSTM-based phonetic recognition generation method. This method first defines input character sets and builds a vector matrix. Then it processes input and computes states by splitting place name words and converting them into vectors. Neural units process the vectors to obtain the current state. Based on this, phonetic conversion is performed using the vector matrix. All obtained phonetics are processed with a softmax function to calculate the probability of each candidate phonetic, and the one with the highest probability is selected. This process is repeated until all phonetics are generated. To handle diverse language habits and word-formation patterns, the study introduces a bidirectional maximum matching algorithm for syllable segmentation. The algorithm first sets the syllable sequence to be segmented as shown in equation (10).

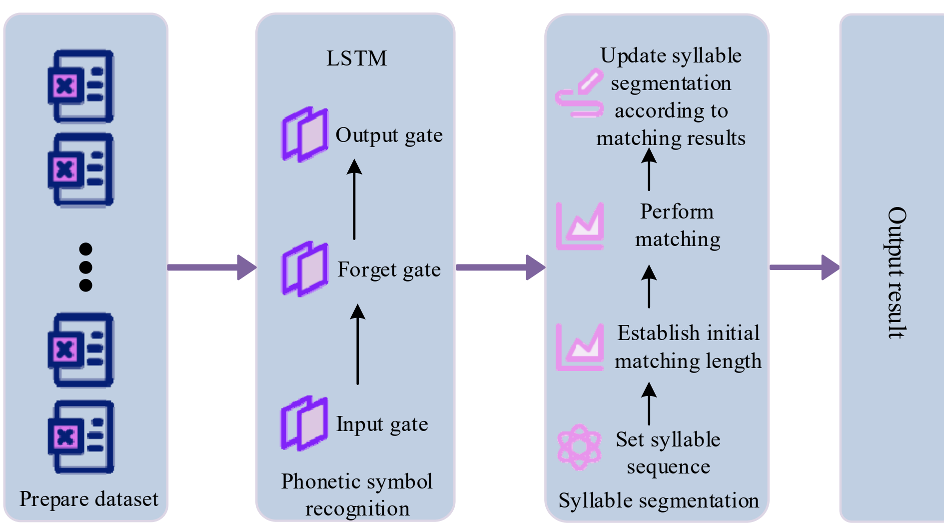
$$S = [S_1, S_2, S_3, \ldots, S_{Length}] \tag{10}$$

In equation (10), *Length* represents the length of the sequence. The syllable dictionary is set as *D*, and the largest syllable in the dictionary is *MaxLen*. This dictionary is a specialised syllable dictionary for place names. Based on publicly available geographic information databases and target corpora, the syllable segmentation results of place names are extracted and deduplicated. Then, the semantic attributes of place names are combined to supplement label information for syllable entries. At the same time, errors in the syllable segmentation of rare place names are manually verified and corrected, ultimately forming a syllable dictionary that covers common and proprietary place names, and is suitable for place name recognition and translation tasks. The initial matching length is set as $Len = \min(Len, MaxLen)$, and a segment of length *Len* is taken from the left side of the sequence, as shown in equation (11).

$$N = S[1 : Len] \tag{11}$$

In equation (11), *N* represents the extracted sequence. Matching and recursive analysis are performed by matching the dictionary with the segmented sequence. If the match is successful, the current sequence is removed. If it fails, the length is reduced and rematched until segmentation is not possible. To improve transliteration accuracy, we apply pronunciation rules after syllable segmentation and use dialect variant mapping tables to address pronunciation differences between American and British English, ensuring standardised and compatible phonetic symbols. The remaining phonetic sequence is then segmented until all phonetics are segmented. The translation model is shown in Figure 5.

Figure 5 Derived place name translation model operation process (see online version for colours)

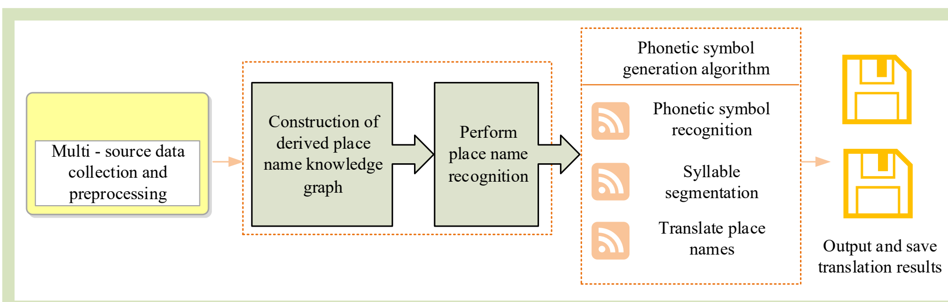


As shown in Figure 5, the model first prepares the dataset of English-derived place names, which provides the basis for translation. It then applies LSTM with input, forget, and output gates to recognise syllables, improving the efficiency and accuracy of phonetic extraction. The bidirectional maximum matching algorithm segments syllables by setting the syllable sequence and initial matching length, increasing translation accuracy and reliability. Finally, the model translates the processed syllables and outputs the translated names.

2.3 Integration and optimisation of the two models

The recognition model based on knowledge graph and the translation model based on phonetic generation algorithm have been constructed, but they often operate independently and lack dynamic collaborative optimisation. With higher precision requirements for English-derived place name recognition and translation, separating semantic mining and phonetic analysis is insufficient for complex derivation rules and multilingual transcription ambiguity (Liu et al., 2023; Nie et al., 2023). This study integrates the recognition and translation models to enhance processing efficiency. The combined model is shown in Figure 6.

Figure 6 Place name recognition and translation model operation process (see online version for colours)



As shown in Figure 6, the model consists of four parts. It first collects and preprocesses English-derived place name data. Then it constructs the knowledge graph for name recognition. After that, the phonetic generation algorithm translates the names, including syllable recognition and segmentation. Finally, the translated names are saved. English-derived place names often contain both generic and specific names. If they are not distinguished, recognition and translation accuracy may decrease (Yang et al., 2024b). Therefore, the study separates generic and specific names as the basis for recognition and translation. The model constructs word feature vectors using term frequency-inverse document frequency (TF-IDF), as shown in equation (12).

$$TF-IDF = TF + IDF = \frac{ni,j}{\sum_k n_k,j} * \log \frac{|N|}{1+\left|\{d \in D : W_{i,g} \in d\}\right|} \tag{12}$$

In equation (12), ni,j is the frequency of the word in the text, and d is the number of documents where it appears. Each word's frequency and rarity across documents are calculated, multiplied to obtain feature weights, and form the document feature vector (Zhang et al., 2023b; Liang et al., 2024). Based on this, clustering is performed using the K-means algorithm, which divides samples into clusters. The algorithm starts with a dataset of size n, sets $I = 1$, selects k cluster centres, and denotes them as $Z_j(I)$. It then calculates the distance between the target object and the cluster centres, denoted as $D(x_i, z_k(I))$. The sum of squared errors criterion is calculated as shown in equation (13).

$$J_c(I) = \sum_{i=1}^{k} \sum_{k=1}^{n_j} \left\| x_k^{(j)} - Z_j(I) \right\|^2 \tag{13}$$

In equation (13), J represents the criterion function. The model checks whether $| Jc(I) - Jc(I-1) | < \xi$ is satisfied. If yes, the process ends. If not, it resets $I = I + 1$ and calculates new cluster centres, as shown in equation (14).

$$Z_j(I) = \frac{1}{n} \sum_{i=1}^{n_j} x_i^{(j)} \tag{14}$$

After obtaining the new cluster centres, the process returns to step two and recalculates the distance for each target object. The clustering result is evaluated using an index as shown in equation (15).

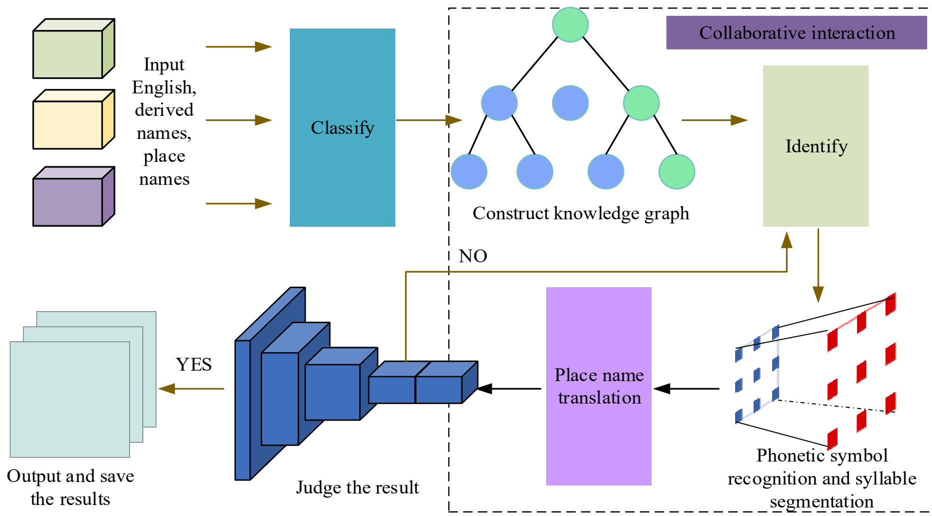
$$A = \frac{\sum \left(\left| 0.5 - \frac{N_G}{Sc} + 0.5 \right) \times Sc}{\sum Sc} \tag{15}$$

In equation (15), Sc represents the number of place names in the cluster, and N_G represents the number of generic names in the cluster. After classification, local search tuning is performed by setting and optimising hyperparameters to improve model accuracy. A hyperparameter is randomly selected from the set, adjusted by a small random value, and validated. If accuracy improves, the change is kept; otherwise, it is reverted. This local search preserves the best classifier and completes the classification process. The optimised combined model based on knowledge graph and phonetic generation algorithm is shown in Figure 7.

In Figure 7, the model first inputs English-derived place names as basic data, then classifies them into generic and specific names. Based on this, the knowledge graph is built to clarify the semantic structure of the names for precise recognition. After recognition, the model uses an LSTM to identify and segment phonemes, linking names to speech. Then it translates the names into the target language. Finally, the translated names are evaluated. If they meet the standard, the result is output; if not, the recognition process is repeated until the final standard is satisfied.

To visually demonstrate the model's workflow, this study employs the English-derived place name 'Granite Lake Drive' as a case study, detailing the complete processing sequence from entity recognition to Chinese transliteration. First, knowledge graph-based entity annotation identifies 'Granite Lake' as a proprietary geographical entity and 'Drive' as a common road name within the dataset, establishing semantic foundations for subsequent processing. Next, the LSTM algorithm analyses textual features to improve the efficiency and accuracy of phonetic transcription. A bidirectional maximum matching algorithm then performs syllable segmentation with an initial matching length of 3, optimising syllable sequences. TF-IDF is applied to extract feature vectors, further clarifying generic name distinctions to prevent confusion. Finally, phonetic transcription and Chinese transliteration are generated using segmented syllables and semantic information, producing the output 'Granite Lake Drive'.

Figure 7 Optimised English-derived place name recognition and translation model (see online version for colours)



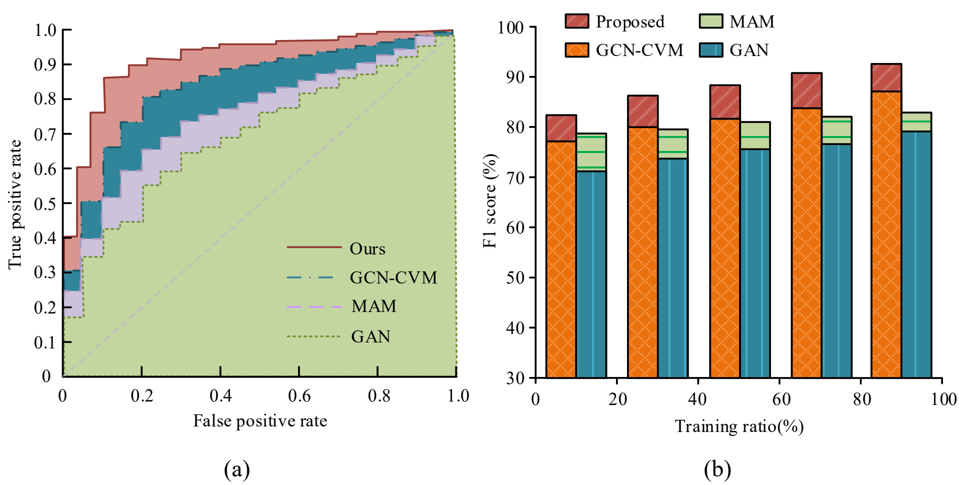
3 Results and analysis

3.1 Performance verification of the recognition and translation model

The study compared the English-derived place name recognition and translation model based on the combination of KG and PGA with the directional graph convolutional network and coefficient of variation method (GCN-CVM) model, the mixed attention mechanism (MAM) model, and the generative adversarial network (GAN) model to verify its superiority. GCN-CVM is a model that has shown strong spatial feature capture ability in graph-structured data tasks related to geographic information in recent years. It is often used as a benchmark for place name tasks. MAM has strong semantic association modelling capabilities in cross-language sequence annotation tasks due to its hybrid attention mechanism and is a typical attention-based benchmark model in this field. GAN, on the other hand, is widely used as a benchmark model for generating performance comparisons in text generation tasks such as place name translation, relying on its generative modelling ability. These three types of models represent the three mainstream technical directions in graph structure modelling, attention mechanisms, and generative modelling, respectively, providing a coverage comparison of the technical path of model research. The experiment used Windows 10 as the system version, Linux 5.15.133 as the operating system, Pytorch as the deep learning framework, Adam as the optimiser, Python 3.10.12 as the programming language, NVIDIA RTX 3080 as the GPU, and 64 GB of memory. In order to ensure the authenticity and reliability of the experiment, the experimental dataset was tested and trained using vector datasets from the states of New York and Washington in the United States. This dataset includes

142,000 vector data, with the training set containing 113,000 and the testing set containing 29,000. In terms of data preprocessing, the research checks the attribute data of vector data and removes vectors with missing place names and land cover category attributes. At the same time, the collected data on English synonyms, semantic inclusion relationships, directional word synonyms, adjective synonyms, compound word synonyms, etc. will be inspected by professionals to remove erroneous semantic relationship data. First, the area under curve (AUC) and F1 score of the four models in the recognition phase were compared. The results were shown in Figure 8.

Figure 8 Comparison of AUC values and F1 scores, (a) AUC value comparison results (b) F1 score comparison results (see online version for colours)



AUC value was an important indicator for evaluating model performance. The closer it was to 1, the better the performance. As shown in Figure 8(a), in the recognition phase, the ROC curve of the study model was closest to the upper left corner, and its AUC reached 0.892, significantly higher than the comparison models' 0.842, 0.786, and 0.723, showing better recognition performance. The F1 score was the harmonic mean of precision and recall. A higher score indicated better performance. As shown in Figure 8(b), the F1 score of the study model remained above 80%, while the comparison models were significantly lower, indicating that the study model achieved a better balance between precision and recall in the recognition phase. Overall, the study model outperformed the comparison algorithms in classification prediction and recall in the recognition phase, demonstrating better robustness. To further evaluate the prediction performance of each recognition model, recognition accuracy and loss curves were compared, and the results were shown in Figure 9.

As shown in Figure 9(a), the study model's recognition accuracy increased steadily during training and reached 98.5% at 20 iterations. It not only had much higher accuracy than the other models, but also showed a smoother curve, indicating its stability. As shown in Figure 9(b), the loss of the study model decreased rapidly and approached 0.2 at 30 iterations, while the other models decreased more slowly, with losses still above 1 at 100 iterations. The GCN-CVM model also showed large training fluctuations, resulting in poor overall efficiency. In summary, the study model showed outstanding data performance in improving recognition accuracy and loss convergence, demonstrating its strong advantages in model performance and its suitability for tasks requiring high efficiency and precision. Next, the error rates of recognition and translation of the four models were compared, as shown in Figure 10.

Figure 9 Accuracy and loss rates of different models, (a) accuracy curve (b) loss curve (see online version for colours)

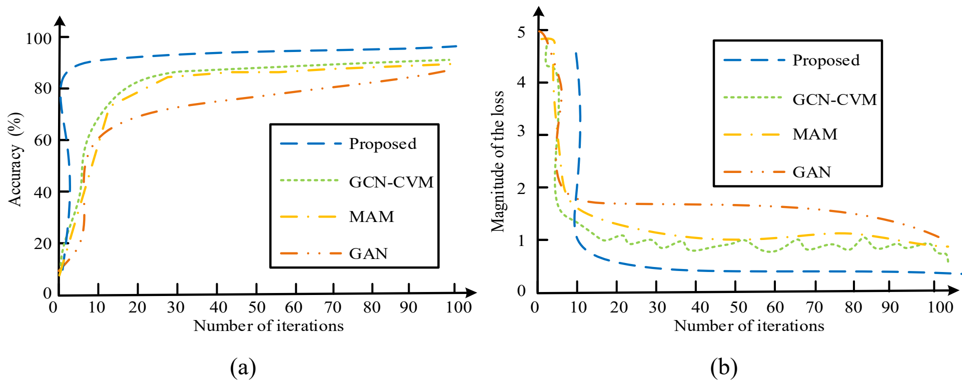
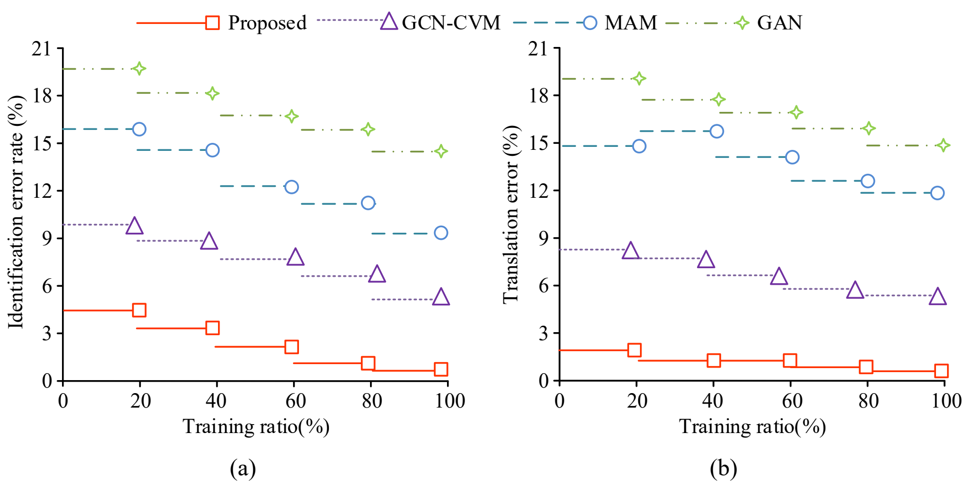
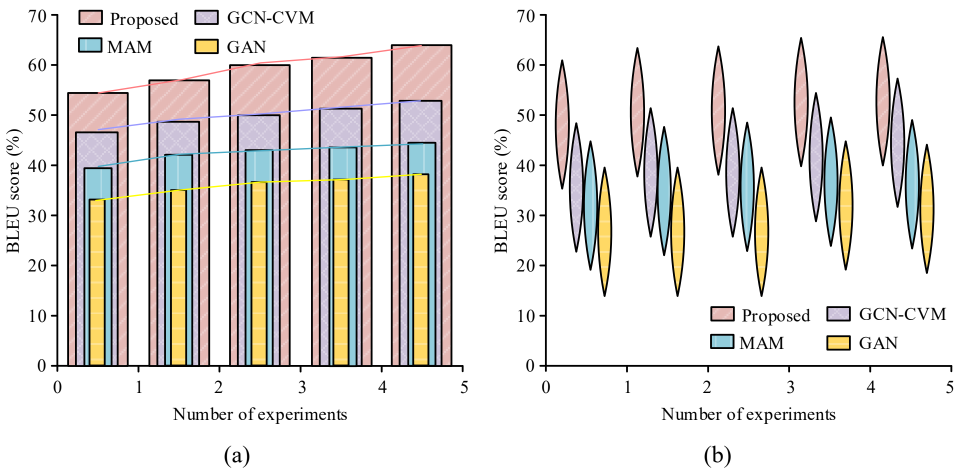


Figure 10 Error rate of translation and recognition, (a) identification error rate curve (b) translate error rate curve (see online version for colours)



As shown in Figure 10(a), when the number of training iterations reached 100, the recognition error rate of the study model was 1.3%, which was 5.5% lower than that of the GCN-CVM model (6.8%), 9.9% lower than that of the MAM model (11.2%), and 14.5% lower than that of the GAN model (15.8%), proving that its recognition performance was the best. As shown in Figure 10(b), after 100 iterations of training, the translation error rate of the study model was only 0.8%, significantly lower than that of the other models, demonstrating its superior translation performance. In summary, the study model had absolute advantages in both recognition and translation tasks, showing stability and reliability. It is worth noting that most errors stem from the lack of recognition of cross-class modification relations, and translation errors are mainly in the translation of multi-layer modification structures of proper place names. Next, the BLEU score of the four models in translation was evaluated, and the results were shown in Figure 11.

Figure 11 BLEU scores of four models, (a) training set (b) test set (see online version for colours)

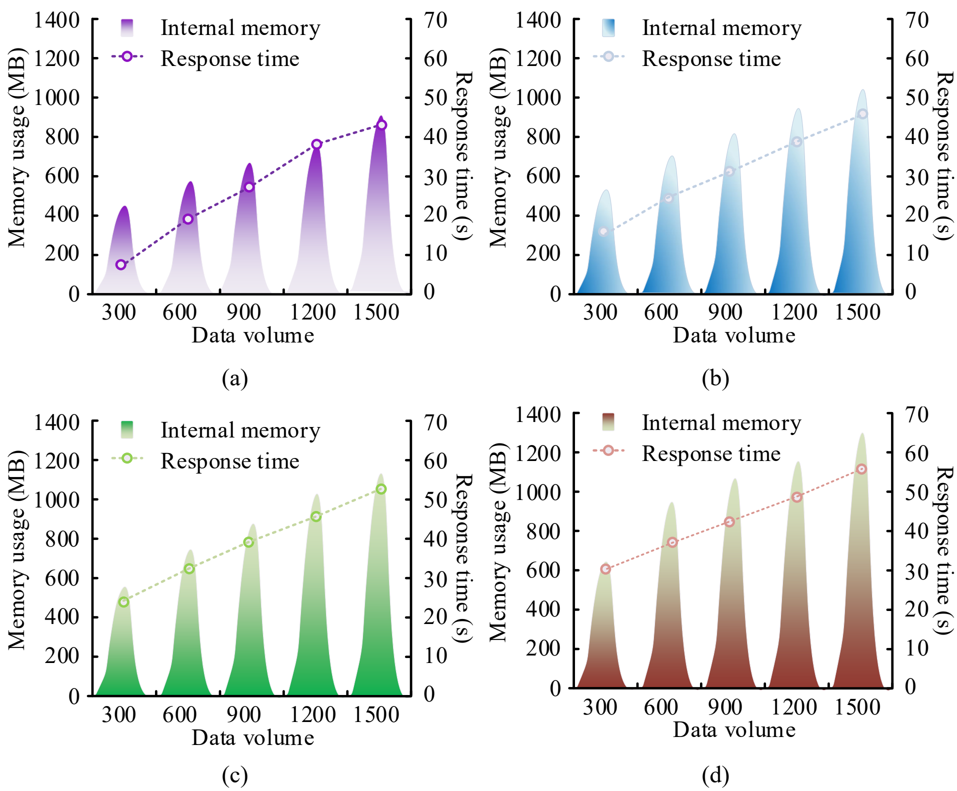


As shown in Figure 11(a), when tested on the training set, the BLEU score of the study model was always the highest in different experiments, reaching 61.3% at the fifth experiment, significantly higher than the other models' 48.7%, 40.6%, and 35.4%. As shown in Figure 11(b), when tested on the test set, the BLEU score of the study model remained the highest, reaching 67.4% at the fifth experiment, which was 11.2% higher than the GCN-CVM model, 20.1% higher than the MAM model, and 25.8% higher than the GAN model. In summary, the BLEU score of the proposed model at the translation level is significantly better than the other three compared models, demonstrating higher translation quality and more stable performance in both the training and testing sets. This result further confirms that the proposed model can not only accurately capture semantic information in place names but also effectively process phonetic recognition and segmentation through phonetic generation algorithms, thereby achieving high-precision place name translation.

3.2 Analysis of practical application effect of recognition and translation model

After verifying the performance of the proposed model, the study further validated its practical application value by collecting derived place names from California and Mississippi and creating a related dataset. The study model was compared with the GCN-CVM, MAM, and GAN models in this dataset. The experiment used the Pytorch framework for training, with Vivado 2012.2 as the development environment and an Intel(R) Silver 4210R CPU @ 2.40 GHz as the simulation environment. First, recognition and translation time and system capacity were compared, and the results were shown in Figure 12.

Figure 12 Comparison of response time and memory usage, (a) proposed (b) GCN-CVM (c) MAM (d) GAN (see online version for colours)



As shown in Figure 12(a), the memory usage of the study model increased slowly, with a maximum usage of 786 MB. When the data volume reached 1500, its response time was only 43.1 s. As shown in Figures 12(b), 12(c), and 12(d), the maximum memory usage of the GCN-CVM, MAM, and GAN models was 52.3 MB, 58.6 MB, and 66.7 MB, and their maximum response times were 48.5 s, 55.9 s, and 58.3 s, all much higher than that of the study model. In summary, the study model demonstrated more stable performance and higher operating efficiency than the other models. To further test the classification ability for derived place names, the classification visualisations of the models were compared, and the results were shown in Figure 13.

As shown in Figure 13(a), the study model classified the sample data of English-derived place names well without missing or misclassifying data. The three comparison models all showed misclassification and omission, and the GAN model even formed a third erroneous class. These models showed worse classification performance compared with the study model. In summary, the proposed model achieved the best classification performance and accurately identified sample data, laying a solid foundation for translation and recognition tasks. Next, the fluency and consistency of recognition and translation of the four models were compared, and the results were shown in Figure 14.

Figure 13 Visual comparison of classification results, (a) proposed (b) GCN-CVM (c) MAM (d) GAN (see online version for colours)

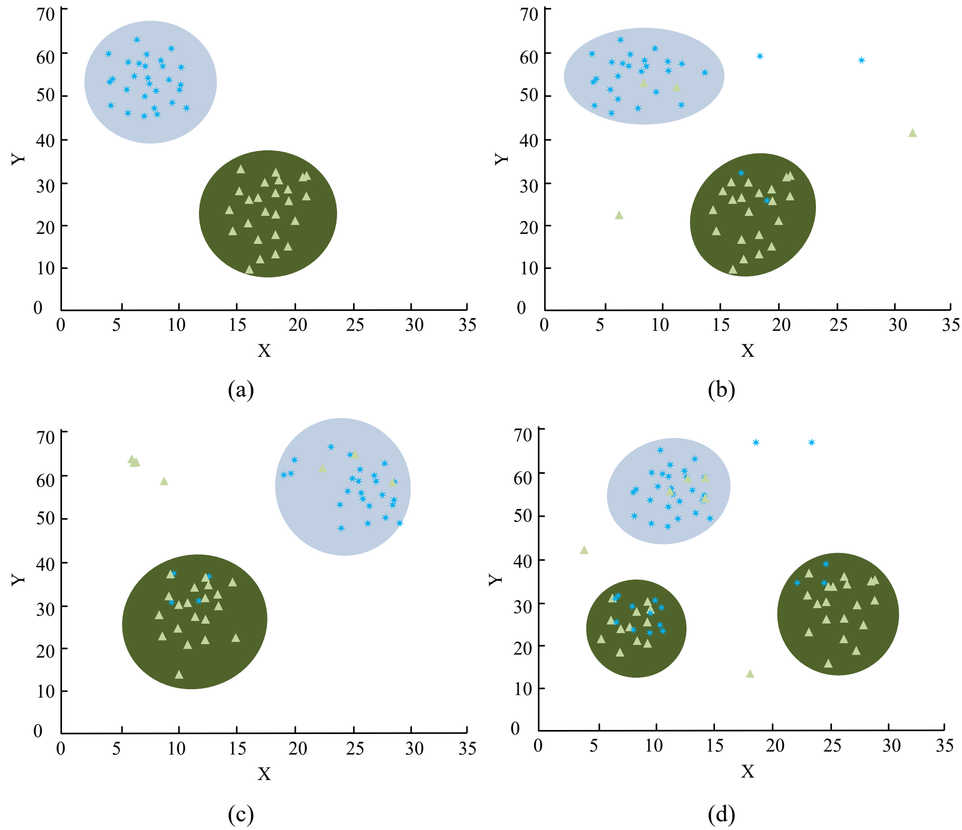
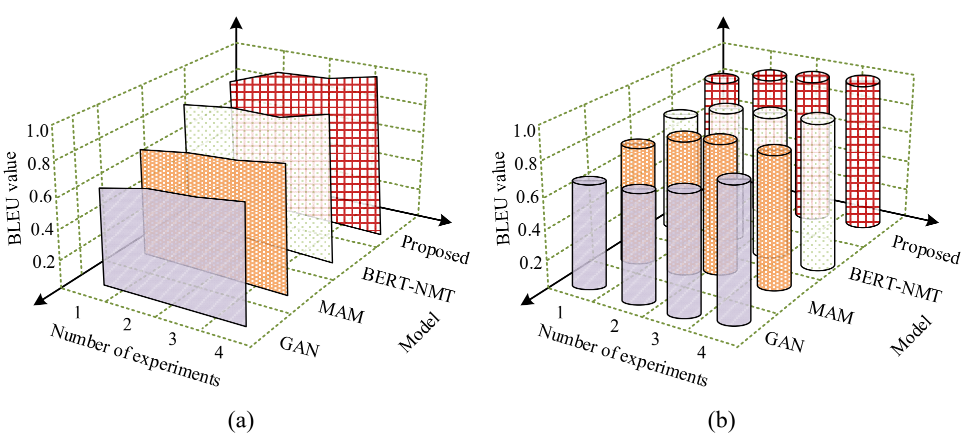


Figure 14 Comparison results of fluency and consistency, (a) smoothness of four models (b) consistency of four models (see online version for colours)



As shown in Figure 14(a), the fluency of the study model was always the highest, reaching 96.8% in the fourth experiment, while the other models were significantly lower. As shown in Figure 14(b), the consistency of recognition and translation of the study model remained the highest, staying above 95.5%. Although the other three models showed an increasing trend with additional experiments, their values remained between 60% and 80%, much lower than those of the study model. In summary, the study model showed better performance in actual recognition and translation and achieved tasks with higher efficiency. Finally, the recognition and translation results of the four models under different data scales were tested, and the results were shown in Table 1.

Table 1 BLEU scores for recognition and translation

Data scale	*Proposed (%)*	*GCN-CVM (%)*	*MAM (%)*	*GAN (%)*
2,000	58.4	52.1	46.1	36.4
4,000	60.6	54.2	47.2	37.1
6,000	61.5	55.8	47.9	37.5
8,000	62.3	56.2	48.2	38.3
10,000	63.7	57.5	48.4	39.6
12,000	64.5	58.2	49.0	40.5

As shown in Table 1, as the data scale increased, the BLEU scores of the four models all improved. The score of the proposed model was always the highest, reaching 64.5% when the data scale was 12,000, far exceeding the comparison models, demonstrating its advantages in high-resource scenarios and large-scale data processing. The other three models lagged behind the study model by more than 6%, proving that their performance in both small-scale and large-scale data processing still needed improvement. In summary, the study model improved translation accuracy through data augmentation and architecture innovation. When applied to different corpus sizes, it achieved breakthroughs in translation precision. The analysis of the practical application results showed that the study model had obvious advantages in actual English-derived place name recognition and translation tasks, offering better stability and more reliable, efficient technical support for related fields and addressing many shortcomings of traditional methods. Finally, to assess whether the differences in the model are statistically significant, the study introduced ablation experiments and t-tests, using KG to represent the knowledge graph. The test results are shown in Table 2.

Table 2 Results of ablation experiments and t-tests for model performance

Comparative model	*AUC value*	*BLEU score*
KG-BMM-LSTM-TF-IDF-K-means	0.894	62.7
KG-BMM-LSTM-TF-IDF	0.868*	61.5*
KG-BMM-LSTM-K-means	0.864*	60.4*
KG-BMM-TF-IDF-K-means	0.852*	58.7**
BMM-LSTM-TF-IDF-K-means	0.747**	57.2**

Notes: * indicates a statistically significant difference compared to KG-BMM-LSTM-TF-IDF-K-means, $p < 0.05$. **There is a significant difference compared to KG-BMM-LSTM-TF-IDF-K-means, $p < 0.01$.

According to Table 2, in the ablation experiment, the AUC value and BLEU score of the complete model were the highest, at 0.894 and 62.7, respectively. After removing each module, both the AUC value and BLUE score decreased, with AUC decreasing by up to 0.147 and BLUE score decreasing by up to 4.5%. The results of the ablation experiment indicate that each module of the knowledge graph and the phonetic generation algorithm has played an important role in improving the model's performance, and that there is a synergistic effect between the modules, jointly enhancing the overall performance. The t-test results indicate that there are statistically significant differences in AUC values and BLEU scores between the complete model and various ablation variants, further confirming the irreplaceability of the knowledge graph and phonetic generation algorithm fusion design. Next, the robustness of the four models was compared, and the comparison results are shown in Figure 15.

Figure 15 Robustness of four models, (a) input noise (b) spelling mistake (see online version for colours)

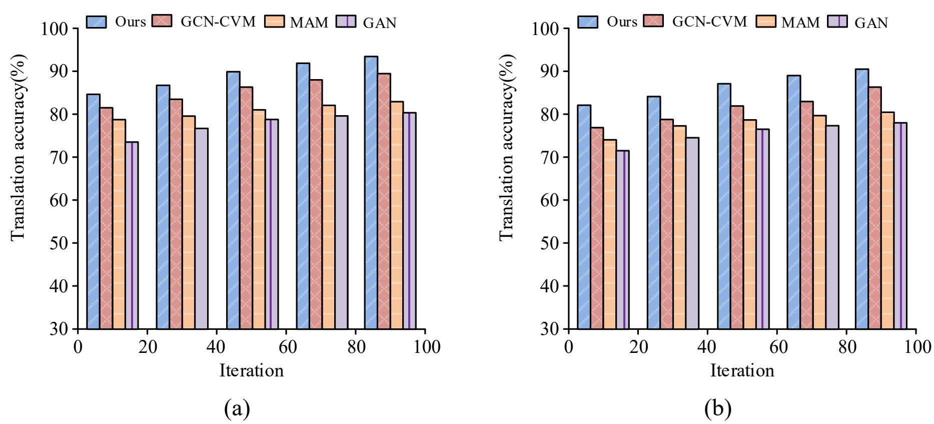


Table 3 Sensitivity analysis results of key parameters in the model

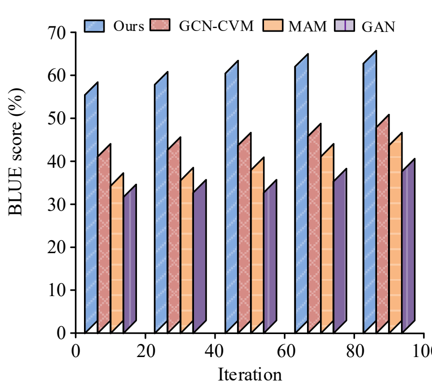
Parameter name	*Specific value*	*Recognition F1 score (%))*	*Translation accuracy (%)*
LSTM learning rate	0.0001	64.5	75.3
	0.001	72.3	82.7
	0.01	88.7	91.6
Knowledge graph entity coverage	50%	85.2	88.9
	70%	90.5	93.4
	90%	92.8	95.7

As shown in Figure 15(a), the proposed model consistently achieved the highest translation accuracy under input noise, reaching 93.2% after iteration, significantly higher than the comparison model. As shown in Figure 15(b), the proposed model still achieved the highest translation accuracy under spelling errors, reaching 90.2% after iteration, while the translation accuracy of the other three comparison models was less than 90%. The above results indicate that the proposed model is more robust in the face of interference factors such as input noise and spelling errors. It can maintain high translation accuracy in complex and varied practical application scenarios, providing strong support for the accurate recognition and translation of English-derived place names. Next, the sensitivity of key parameters in the model was analysed, and the comparison results are shown in Table 3.

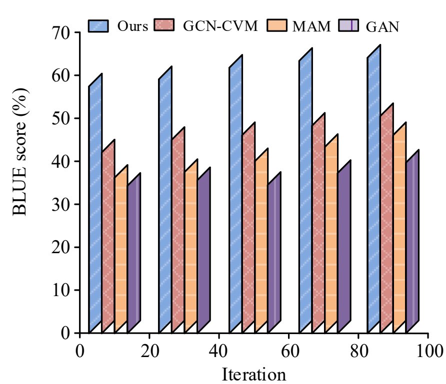
According to Table 3, when the LSTM learning rate increases from 0.0001 to 0.01, the recognition F1 value increases from 64.5% to 88.7%, and the translation accuracy also increases from 75.3% to 91.6%. This change indicates that increasing the LSTM learning rate appropriately can help the model better capture data features, thereby improving its performance in practical applications. Meanwhile, as the entity coverage of the knowledge graph increases from 50% to 90%, the recognition F1 value and translation accuracy increase from 85.2% and 88.9% to 92.8% and 95.7%, respectively. This indicates that rich knowledge graph entity information can provide more contextual clues for the model, which helps the model to more accurately identify and translate English-derived place names. The above results indicate that the key parameters of the model have a significant impact on recognition and translation performance. By adjusting the LSTM learning rate and knowledge graph entity coverage reasonably, the performance of the model in practical applications can be effectively improved. In order to evaluate the generalisation ability of the model, cross domain testing was added and English-derived place name datasets from two different fields, tourism and history, were selected for testing. The comparison results are shown in Figure 16.

As shown in Figure 16(a), in historical texts, the BLUE score of the proposed model is in a leading position. After the iteration is completed, its BLUE score reaches 66.7%, while other models are less than 50%. As shown in Figure 13(b), the proposed model performs better in tourism related texts, reaching over 60% initially and 68.2% after iteration, significantly higher than the comparison model. The experimental results show that the proposed model also demonstrates excellent generalisation ability in cross domain testing, and its translation quality is significantly better than other comparative models for both historical and tourism texts. This achievement not only verifies the stability and adaptability of the model in handling English-derived place names in different fields, but also further expands the application scope of the model.

Figure 16 BLUE scores of the model in different domains of text, (a) history (b) travel (see online version for colours)



(a)



(b)

4 Discussion and interpretation

The proposed model for English-derived place name recognition and translation showed significant advantages in the performance comparison experiments. In terms of error value and BLEU score, the proposed model outperformed the three comparison models, GCN-CVM, MAM, and GAN. This was mainly because the designed knowledge graph had a stronger data processing ability. A similar conclusion was drawn in the study on machine translation with reinforcement learning conducted by A. Kumar et al. in 2023, which proved that enhancing data processing significantly improved the performance of machine translation models (Zhu et al., 2024b). In addition, the proposed model also showed strong superiority in AUC value, loss convergence, and F1 score. Compared with the three models, its AUC value reached 0.892, which was closest to 1. The loss approached 0.2 after 30 iterations, and the F1 score in the test set reached 61.3%, which was much higher than the other models with 48.7%, 40.6%, and 35.4%. This mainly benefited from the proposed model integrating LSTM and the bidirectional matching maximum algorithm, which enhanced the global search ability of the model and achieved a coordinated improvement in precision and recall. The above results were similar to the results obtained by organisation raised by Dalva et al. (2023), where their recognition and translation accuracy maintained a high level, which verified the effectiveness of knowledge-driven models in language processing tasks (Zhou et al., 2024; Zhang et al., 2023c).

In the empirical study of English-derived place name recognition and translation, the proposed model also showed significant advantages. Under different data scales, the proposed model outperformed the three comparison models, GCN-CVM, MAM, and GAN, in BLEU score, memory usage, and response time. Its fluency reached 96.8%, and consistency remained above 95.5%. This was mainly because the proposed model integrated recognition and translation models to build a more accurate recognition and translation framework, improving the efficiency of English-derived place name processing. Compared with related studies, the proposed model showed a more obvious improvement in performance. For example, compared with the recognition and translation model with word alignment structure raised by Xi et al. in 2024, the proposed model improved efficiency and quality by several percentage points when handling large data (Oza et al., 2024). Compared with the semantic-aware model raised by Yang et al. (2024b), the proposed model further improved translation consistency and better captured semantics (Hasanvand et al., 2023). Meanwhile, the proposed model adopted the TF-IDF method with the K-means algorithm for data classification, which optimised the process from data preprocessing to core task execution. Compared with the results on short text classification raised by Y. Zhu et al., the proposed model further improved classification accuracy and quality without misclassified or wrongly classified samples (Hasanvand et al., 2023). Overall, the study put forward a new and more efficient method for English-derived place name translation and recognition, which had the potential to promote the intelligent upgrade of related application scenarios.

The innovation and contribution of the research are mainly reflected in the following three aspects. In the linguistic dimension, the study provides a new method for linguistic analysis of English-derived place names through the integration of knowledge graph and phonetic generation algorithm; In the dimension of geographic information science, the proposed model for translating and recognising place names has improved the accuracy of matching place name information in the field of geographic information; In the dimension of computer linguistics, the practical application of the proposed model has verified its effectiveness, providing a practical paradigm for the landing of place name processing in computer linguistics.

5 Summary and future work

The proposed model addressed the problems of traditional English-derived place name translation and recognition models, which lacked semantic and phonetic alignment, had low recognition and translation accuracy, and could not handle large-scale data effectively. The study proposed a recognition and translation model that combined a knowledge graph and a phonetic generation algorithm. It integrated multiple algorithms to achieve deep semantic and phonetic alignment between the source and target languages. Experimental data showed that the proposed model outperformed the comparison models in AUC value, F1 score, and recognition accuracy. In addition, the analysis of its practical application showed that the proposed model consumed less time and memory and had the best classification performance, which proved its superiority in real translation and recognition tasks. Overall, the proposed model effectively handled the translation and recognition of English-derived place names and showed unparalleled application performance. This study did not test multiple languages, so the experimental results had certain limitations. Therefore, in future research, derived place name vocabulary from Indo-European and Sino-Tibetan language families can be selected to construct a multilingual test set, and combined with pre-trained multilingual models, transfer learning strategies for derived word meanings, phonetics, and features can be designed to reduce dependence on minority languages. Resource imbalance can also be solved through data augmentation, cross-linguistic knowledge distillation, and other methods, thereby improving the model's multilingual adaptability and practical application value.

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Declarations

The author declares no conflicts of interest.

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