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Assessment of the Quality of Social Public Services from a Community Perspective Based on Deep Learning Models and Attention Mechanisms

Yu Yuan[1,*]

[1]School of Sociology and Population,
Renmin University of China, Beijing 100872, China
1421803218@qq.com

Chen Lixin[2]

[2]University of Central Lancashire Preston,
Preston PR1 2HE, UK
LChen30@uclan.ac.uk

*Corresponding author: Yu Yuan

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Abstract. *In the realm of governmental public management, propelled by the rapid advancement of information technology, big data emerges as an indispensable tool for fostering societal development. Community services, integral to governmental operations, directly impact the well-being of the populace. Hence, the quality of community services significantly influences public satisfaction with governmental provision of public services. This study proposes an evaluation method for community public service (CPS) quality based on BERT model and attention mechanisms. Through aspect-based sentiment analysis (ABSA) of public feedback texts, satisfaction with CPS is automatically assessed across five dimensions: service efficiency, attitude, fairness, transparency, and sustainability. Within the proposed deep learning framework, comments are initially processed through BERT to derive contextual sequence vectors, aspect word sequence vectors, and global sentence vectors. Subsequently, these vectors are fed into a local feature extractor to comprehensively capture semantic features. Finally, the obtained context-aspect representations are jointly subjected to multi-head attention calculation with global sentences, incorporating a feature fusion structure based on Conditional Layer Normalization (CLN) to better integrate local and global features. Experimental results on a dataset of CPS feedbacks demonstrate the efficacy of the proposed method in accurately evaluating various aspects of CPS quality. This approach facilitates a nuanced understanding of the strengths and weaknesses across different facets of societal public service, providing governmental departments and relevant entities with scientifically sound decision-making support. Furthermore, it offers valuable insights and references for further research and practice in the domain of social public service quality assessment.*
Keywords: Community public service; Aspect-based sentiment analysis; BERT; Attention mechanism; Conditional Layer Normalization.

1. **Introduction.** With the continuous development and progress of society, public services are crucial for ensuring social equity and promoting social welfare. From the perspective of communities, which are both direct beneficiaries and participants of public services, the evaluation of community public service (CPS) quality becomes particularly significant [1]. As information technology rapidly advances, big data gradually emerges

as an indispensable tool in governmental public management, becoming one of the pivotal instruments for fostering societal development. In recent years, China has vigorously implemented its "national big data strategy," advancing the implementation of this strategy as an essential pathway to enhance the country's digital infrastructure [2]. This strategy promotes data openness, sharing, and resource integration, safeguarding national data security and better promoting economic and social development, thus continually improving people's living standards.

In the practical requirements of advancing the implementation of the national big data strategy, it is emphasized to utilize big data to enhance the modernization of national governance and to promote the safeguarding and improvement of people's livelihoods. The quality of CPS is closely related to the happiness and satisfaction of the people. Only by fulfilling regulatory responsibilities in accordance with the law, continuously improving regulatory methods, and prioritizing the enhancement of public satisfaction, can the quality of public services be improved, thereby achieving the goal of safeguarding and improving people's livelihoods [3]. In today's era of rapid informatization, studying CPS quality cannot be separated from the support of big data.

Existing methods for evaluating the quality of CPS mainly involve the formulation of performance management assessments, the construction of performance evaluation indicators, and the establishment of public satisfaction evaluation models [4]. However, there have been fewer studies on automatically evaluating the quality of CPS using big data and deep learning (DL) technologies. Traditional methods often suffer from a single perspective, whereas applying big data technology to evaluate CPS quality, utilizing sentiment analysis (SA) methods to extract people's demands, calculating sentiment scores, and exploring the applicability can intuitively demonstrate people's satisfaction with the quality of CPS. This facilitates the analysis of shortcomings in various departments' work in the public service sector, enabling targeted improvements in the quality of CPS.

Currently, there is a plethora of feedback text regarding CPS on the internet, sourced from various channels such as social media platforms, online forums, and review websites. These texts typically encompass a range of opinions, views, and emotional experiences of community residents, reflecting the real-life situation of public service quality, efficiency, and attitudes. Conducting aspect-based sentiment analysis (ABSA) on this data holds significant value [5].

Firstly, these comments objectively reflect community residents' needs and satisfaction. Feedback texts posted by community residents on the internet objectively depict their demands and satisfaction with public services. Through ABSA, emotional information embedded in the texts can be thoroughly explored, accurately discerning community residents' attitudes and emotional inclinations towards various aspects of CPS, thereby providing vital insights for governmental departments and relevant agencies to improve services.

Secondly, ABSA can help identify problems and areas for improvement in CPS. By analyzing specific aspect terms mentioned in the texts, dissatisfaction with service quality in particular areas can be pinpointed, enabling targeted improvement measures to be proposed, thus enhancing the quality of public services and user satisfaction.

Thirdly, feedback texts posted on the internet may involve unforeseen events or public relations crises that negatively impact the quality of CPS. ABSA can help promptly capture these negative sentiments, assisting governmental departments and relevant agencies in timely response and effective crisis resolution to maintain social stability.

Finally, applying ABSA to the processing of CPS feedback texts aids in establishing a quality monitoring mechanism for public services. Through continuous analysis and monitoring of community residents' feedback, service issues and improvement needs can be promptly identified, facilitating continuous supervision and enhancement of CPS quality.

Traditional SA research primarily focuses on identifying the overall sentiment polarity of entire sentences or documents. This prediction typically conveys a singular sentiment for a single topic within a given material, whether it be a sentence or an entire document [6]. However, reality often entails the expression of multiple sentiments within a single sentence or document. Within a sentence, there may exist various aspects of sentiment, necessitating a finer-grained recognition of aspect-level opinions and emotions, known as ABSA, which has garnered increasing attention [7].

In existing ABSA methods, the goal shifts from expressing sentiment from a single sentence or document to a specific entity or aspect within an entity [8]. In the realm of CPS, an entity could be a concrete hardware facility. For instance, in the sentence, "The environment of the community park is pleasant and clean, but the maintenance of the recreational facilities is inadequate, some of which have been damaged for several days," the comment pertains to the recreational facilities of the community park, with "inadequate maintenance" and "damage" representing specific aspects. The primary research direction of ABSA is to identify various aspect-level sentiment elements, including aspect terms, opinion words, and sentiment polarity. For example, in the sentence, "The attitude of the doctors at the community health station is very friendly, but the waiting time is too long and needs improvement," we have two aspect terms: "doctor attitude" and "waiting time," along with corresponding opinion words: "friendly" and "too long." This example illustrates the commenter's positive viewpoint on the aspect of doctor attitude, indicating that the doctors' attitude is very friendly. However, the opinion regarding the waiting time aspect is negative, suggesting that the wait time is too long and requires improvement. ABSA involves the process of building a comprehensive overview of opinions at the aspect level, providing useful fine-grained sentiment information for service quality assessment.

Although existing models demonstrate commendable performance in ABSA tasks, there are still some shortcomings. Firstly, the importance of aspect terms has not been adequately emphasized. Secondly, in the process of extracting text features, the advantages of local features and global features have not been fully utilized. The sentiment polarity of aspect terms is more closely related to words in absolute and logical proximity, with distant words often becoming interference in sentiment classification.

1.1. **Related Work.** In contemporary governance, big data has gradually permeated into the daily operations of governments. Aradau [9] noted that an increasing number of government officials utilized computational language and methods for their tasks. Big data and associated advanced technologies are now capable of providing insights into the future to address various security issues, including governmental information security concerns. Mariusz [10] introduced the concept of big data and the possibilities of its usage in the public sector, emphasizing the utilization scenarios and outcomes of such data. Additionally, the application of big data methods in public policy design, implementation, and market regulation is briefly outlined. Brayne [11] proposed that employing big data analysis aids in broadening the proactive monitoring practices of public services and fundamentally transforming monitoring activities. Based on risk assessment, data prediction, automatic alerts, collaborative participation, and data sharing, a theoretical model for big data surveillance is designed.

As a crucial research direction in the field of text mining, the development of SA technology and related tools is of paramount importance. Based on the different objects of analysis, SA is classified into three types: document-level, sentence-level, and aspect-level [12]. Document-level and sentence-level SA methods aim to provide the sentiment polarity of entire documents or sentences. These two types of SA tasks assume that a piece of text expresses only one viewpoint, overlooking the possibility that a document may convey multiple viewpoints. Furthermore, they only offer the overall sentiment polarity of sentences or documents without indicating the subject of the emotion, rendering them unsuitable for analyzing evaluations with fine-grained sentiment polarity, such as CPS quality assessment.

ABSA determines people's attitudes towards specific aspects by extracting explicit aspects and detecting the sentiment polarity of each extracted aspect term [13]. Early methods attempted to address this through dictionary and rule-based approaches. Hu [14] searched for relevant sentiment sentences for each aspect term and then determined the sentiment polarity of sentiment sentences based on sentiment seed words and the WordNet dictionary, followed by summarizing aspect sentiment information. Kim [15] considered the sentiment word polarity and intensity for each aspect term and calculated sentiment scores using a multiplication rule. Thet et al. [16] utilized the SentiWordNet sentiment lexicon to determine the sentiment polarity and intensity of each spect in comments. ABSA methods based on traditional machine learning (ML) models primarily rely on manually extracted features. Kiritchenko et al. [17] trained a linear Support Vector Machine (SVM) classifier by using sentiment lexicons and mined syntax trees as features to achieve sentiment classification. Poria et al. [18] designed rules to obtain aspect terms, which were then inputted into ML models to infer sentiment polarity.

Due to its ability to automatically combine low-level features to generate more complex abstract high-level features, thus avoiding extensive manual feature engineering, DL models have received widespread attention and research. Tang et al. [19] utilized two Long Short-Term Memory (LSTM) networks to obtain semantic vectors for the preceding and following contexts, respectively, then concatenated these vectors for sentiment classification. However, this model performed poorly on complex long sentences and was prone to losing sentiment information from distant words. With the rise of attention mechanisms, some studies in multi-aspect multi-sentiment analysis have adopted a combination of attention mechanisms and DL models to classify sentiments by leveraging the relationships between aspects and contexts. Wang et al. [20] proposed an attention mechanism to highlight important information related to specific aspects, concatenating aspect embeddings with input word vectors and inputting them into LSTM to strengthen the feature extraction. However, unidirectional LSTM can only capture preceding context information, and this simple attention mechanism is prone to attention dispersion. Ma et al. [21] designed intricate interactive attention networks, employing two LSTM networks to encode sentences and aspects separately, then interactively learning representations for aspect words and sentences, subsequently combined for sentiment classification. Hu et al. [22] discovered that attention in multi-aspect SA tasks is prone to dispersion due to noise data and the influence of sentiment words from other aspects. Consequently, they proposed a hard selection method to more precisely locate corresponding sentiment word fragments, thereby accurately predicting the sentiment polarity of given aspect words. Tay et al. [23] modeled the relationship between aspects and context words in sentences, inputting aspect category information into the model, and predicting sentiment polarity based on their relationship with the correct sentiment information. Hu et al. [24] addressed the issue of attention being diverted to sentiment words from other aspect categories in sentences, leading to a decrease in accuracy in identifying attribute sentiment polarity. They proposed constrained attention networks to regularize attention in multi-aspect SA tasks.

Li et al. [25] identified the sentiment polarity of words in a given sentence, then identified words representing an aspect category as key elements, and combined the sentiment polarity of these key elements to obtain the sentiment polarity of the attribute aspect.

In recent years, Pretrained language models (PLM) have demonstrated significant performance in many tasks and has become a foundational model in ABSA tasks, with several solutions based on PLM being proposed. Peng et al. [26] utilized BERT as an encoder and proposed a collaborative gating mechanism to enhance the extraction capability of interaction features between aspect words and context. Wu et al. [27] introduced a novel Transformer-based multi-aspect modeling approach, where multiple aspect words were concatenated with sentences to form new text sequences input into BERT or RoBERTa, capturing potential relationships between multiple aspect and identifying the sentiment of all aspect words in the sentence. Based on multiple PLMs, Zhou et al. [28] employed a weighted voting strategy to heuristically combine results from different models to obtain the final result of the overall model. However, this integration method suffers from drawbacks such as large overall model scale, high complexity, and relatively low efficiency. Fei et al. [29] jointly encoded text and multiple aspect category labels using BERT, and thoroughly explored information clues for each aspect category through graph neural networks (GNN), ultimately predicting aspect category sentiment polarity based on contextual representations. Addressing the issue of additional noise introduced by attention mechanisms in multi-aspect sentences and the dilution of sentiment words by other words, Hu et al. [30] proposed mixed regularization strategy to constrain attention weights and alleviate noise.

1.2. **Contribution.** Our research methodology primarily relies on the BERT model, employing ABSA techniques to evaluate various aspects of CPS. ABSA model enables the identification of sentiments expressed in text and associates them with specific aspects, thereby aiding in a deeper understanding of community attitudes and sentiment tendencies towards public services. By leveraging the robust representation capabilities and attention mechanisms of the BERT model, we can more accurately capture key information in the text, facilitating a detailed assessment of the quality of CPS. The main contributions of this paper are outlined as follows:

1) Combining DL models with ABSA has achieved automation and precision in evaluating the quality of CPS. By considering community needs and feedback comprehensively, a better understanding of the strengths and weaknesses of various aspects of CPS is attained, thereby providing government departments and related agencies with scientifically effective decision support to continuously enhance the quality and efficiency of public services, promoting harmonious and stable social development.
2) In ABSA tasks, leveraging BERT to obtain high-quality semantic encoding, a local feature extraction module focusing on features more relevant to aspect words semantically is designed, upon which local feature attention scores are computed. In the feature fusion stage, a combination structure of multiple conditional layer normalizations (CLN) is employed to emphasize balancing local and global features while avoiding feature loss during fusion, thus reinforcing the model's fitting capability.

2. Research background.

2.1. **Definition of Community.** In the "Opinions on Promoting Urban Community Construction Nationwide" issued by the Chinese Ministry of Civil Affairs, a community refers to a collective composed of people living in a related area. Generally, communities possess the following elements [31]:

- **Territorial elements**: Communities have specific requirements regarding the scope of their territory.
- **Demographic elements**: There are certain requirements regarding the population size for a community to be recognized as such.
- **Organizational elements**: The number of community organizations needs to meet certain requirements.
- **Commonality elements**: There are commonalities among residents within the community.

2.2. **Public services.** So far, there has not been a definitive definition of CPS, with different scholars offering varying perspectives, each with a different analytical focus. Some scholars focus on exploring government responsibilities, viewing the government as the main provider of public services. Others pay more attention to the utility of the community, believing that the community's power cannot be overlooked in the process of public service provision. Additionally, some scholars argue that the subject of community public service supply should not be singular but should have a diverse character [32].

Urban CPS provision possesses characteristics of publicness and comprehensiveness. A single entity cannot adequately fulfill this responsibility, necessitating the utility of multiple entities to achieve service objectives. Urban CPS have the following characteristics:

- **Public welfare feature**: Requiring the government to proactively provide these services.
- **Socialization feature**: With the government playing a leading role in planning for areas where the market cannot intervene.
- **Diversity feature**: With the scope of community public services continually expanding and becoming more diverse.
- **Service feature**: Requiring the full utilization of all resources to optimize the CPS system, ensuring residents' needs are met and social benefits are not overlooked.

In summary, CPS mainly refer to employment, culture, education, assistance, family planning, community safety, social security, and other services provided by grassroots governments and their branches to meet the basic needs of residents in the community.

2.3. **Bert.** At the core of BERT lies a Transformer language model, which consists of a specific number of encoder and decoder layers along with a self-attention mechanism [33]. Similar to the Transformer model, BERT conducts bidirectional processing of the text. This enables a better understanding of the contextual relationships of the analyzed words. To optimize BERT for specific NLP tasks with relatively small datasets, a common approach is to fine-tune the model. The deep neural networks (DNNs) used for the BERT model consist of multiple layers of neurons, capable of describing various complex relationships.

The input format of BERT is as depicted in Figure 1. In particular, [CLS] denotes the first token, [SEP] acts as a sequence delimiter, and [MASK] signifies the token used for masking words. Token Embeddings represent the vocabulary ID, Sentence Embeddings differentiate between sentences, and Transformer position Embeddings indicate the position of each word.

2.4. **Attention mechanism.** In ABSA tasks, the role of attention mechanisms is to assist models in better understanding the correlation between different aspects and sentiments in the text [34]. Specifically, the role is manifested in:

- **Aspect perception**: Identifying vocabulary relevant to the target aspect.
- **Sentiment association**: Determining key phrases related to sentiment.
- **Enhancing accuracy**: Focusing on relevant parts to reduce noise.

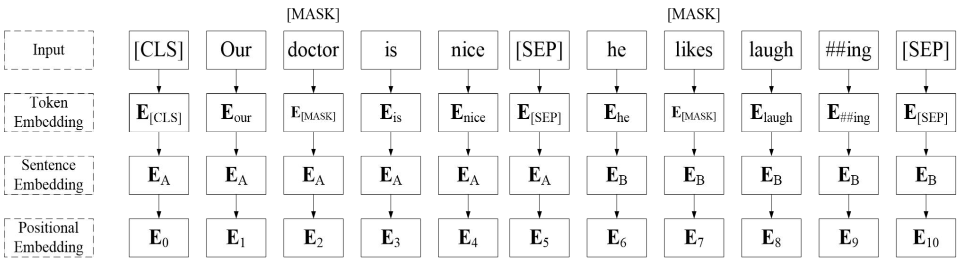

Figure 1. BERT input format illustration.

Given an input text sequence $X = \{x_1, x_2, \ldots, x_n\}$, where n is the length of the sequence and x_i is the i-th word or token, attention mechanisms can calculate the attention weights α_i^A for each word x_i with respect to aspect A.

A common way for calculating attention weights is using an Attention Function. Given the current text representation h_i (word vector or hidden state) and the aspect representation v_A:

$$\alpha_i^A = \text{Attention}(h_i, v_A) \tag{1}$$

where Attention() takes h_i and v_A as inputs to generate weights. Subsequently, these weights are utilized to compute the text representation relevant to aspect A, denoted as $\hat{v}_A$, by performing a weighted average:

$$\hat{v}_A = \sum_{i=1}^{n} \alpha_i^A h_i \tag{2}$$

Thus, the resulting $\hat{v}_A$ is the text representation weighted by the attention considering aspect A. This representation can be utilized for subsequent ABSA tasks.

3. **Proposed method.** The goal of the proposed method is to predict the sentiment polarity of m aspect terms in n CPS-related comment sentences, where sentiment polarity is represented as: Polarity $= \{1, 0, -1\}$, where 1 denotes positive, 0 denotes neutral, and -1 denotes negative. The overall architecture of the model is illustrated in Figure 2 and can be broadly divided into three layers: input layer, feature extraction layer, and output layer. Given a comment sentence, the model takes three inputs for ABSA: local context sequences, aspect term sequences, and global sentence sequences. The comment sentence $S = (s_1, s_2, \ldots, s_n)$ is fed into BERT to convert words into vectors, resulting in vectors for local context sequences (LCS), aspect term sequences (ATS) and global sentence sequences (GSS). The LCS is defined as $C = (c_1, c_2, \ldots, c_t)$, where t contains m aspect terms. Its structure consists of partial words from the right side of the aspect term in the sentence, the aspect term itself, and partial words from the left side of the aspect term. The ATS is defined as $A = (a_1, a_2, \ldots, a_m)$. The GSS is defined as $G = (g_1, g_2, \ldots, g_n)$. The feature extraction layer further comprises local and global feature extraction modules, used to acquire local features of context and aspect terms, as well as dynamically weighted features of the global context. Subsequently, CLN is employed to enhance the feature transmission process, enrich semantic feature expression, preserve original feature information, and directional features, thus achieving feature fusion. Finally, the fused features are input into a linear classification layer for ABSA, utilizing a Softmax layer to predict sentiment polarity.

3.1. **Input layer.** To better utilize the BERT model for training, the LCS is transformed into "[CLS]" + left + aspect + right + "[SEP]". The ATS is transformed into "[CLS]" + aspect + "[SEP]". The GSS is transformed into "[CLS]" + left + aspect + right + "[SEP]"

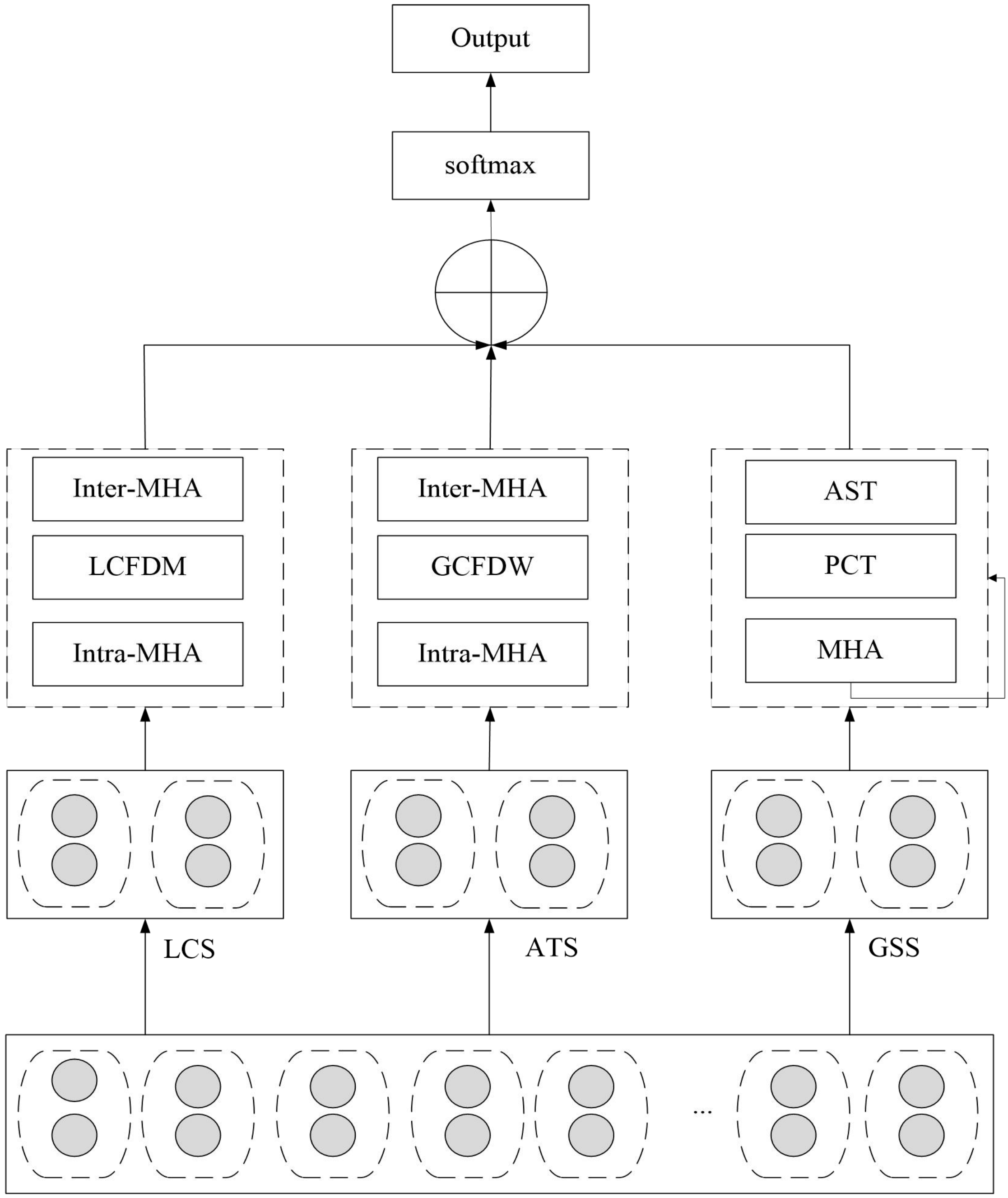

Figure 2. Illustration of the Proposed method.

+ aspect + "[SEP]". The processed LCS, aspect ATS, and GSS are then converted into word vectors using BERT. The LCS is converted into $V_c = \{v_{c_1}, v_{c_2}, \ldots, v_{c_t}\} \in \mathbb{R}^{t\times d}$, where t represents the number of LCS vectors, and d represents the output vector dimension of BERT. The ATS is converted into $V_a = \{v_{a_1}, v_{a_2}, \ldots, v_{a_m}\} \in \mathbb{R}^{m\times d}$, where m represents the number of aspect terms. The GSS is converted into $V_g = \{v_{g_1}, v_{g_2}, \ldots, v_{g_n}\} \in \mathbb{R}^{n\times d}$, where n represents the number of GSS vectors.

3.2. **Attention coding.** The attention encoder is a parallelizable computational structure utilized for extracting hidden features from input vectors. This layer comprises multiple sub-modules, including Multi-head Attention (MHA), Intra-Multihead-attention

(Intra-MHA), Inter-Multihead-attention (Inter-MHA), Local Context Features Dynamic Mask (LCFDM), Global Context Features Dynamic Weighted (GCFDW), Multi-head Attention (MHA) Point-Wise Convolution Transformation (PCT), and Aspect Specific Transformation (AST) modules.

MHA refers to a method capable of parallelizing the computation of multi-head attention [35]. The attention function can be abstractly described as mapping a query sequence $Q = \{q_1, q_2, \ldots, q_n\}$ to keys vector $K = \{k_1, k_2, \ldots, k_m\}$ and values vector $V = \{v_1, v_2, \ldots, v_m\}$, computing the output as the weighted sum of values, where the attention weights assigned to V are obtained from a similarity function between the query q_i and the keys K. Simultaneously, attention functions are computed for a set of queries Q:

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3}$$

where d_k represents the dimensionality of q and k, and $\sqrt{d_k}$ represents the scaling factor to prevent the inner product from being too large.

The MHA can simultaneously focus on word information from different positions in the sentence, thereby attending to information from different representation subspaces. By mapping each element in the input to dimensions d_k and d_v through different linear transformations, and then performing the attention function, we obtain the representation vector of a single attention head:

$$\mathrm{head}_i = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V) \tag{4}$$

After parallel computation, multiple output vectors of attention heads are obtained. Finally, these outputs are concatenated and then transformed through linear transformation to achieve the desired dimensionality:

$$\mathrm{MHA}(Q, K, V) = \tanh(\{\mathrm{head}_1 \oplus \mathrm{head}_2 \oplus \cdots \oplus \mathrm{head}_h\} \cdot W^O) \tag{5}$$

where $\oplus$ denotes the concatenation operation of vectors. h represents the number of attention heads.

Intra-MHA, while extracting the inherent dependencies of words within sentences, learns important features from different heads [36]. It can selectively emphasize features that are relatively important in the sentence. The obtained vectors are first fed into Intra-MHA. The structure of Intra-MHA is illustrated in Figure 3, which combines the distinct characteristics of self-attention and MHA.

In Intra-MHA, each head of the MHA is essentially an individual self-attention mechanism. After computing the output for each head separately, the results are concatenated to form the final output. First, individual self-attention calculations are performed for each head:

$$h_i = \mathrm{attention}(v_{c_i}, v_{c_i}) = \frac{\exp f(v_{c_i})}{\sum_{i=1}^{n} \exp f(v_{c_i})} \tag{6}$$

$$f(v_{c_i}) = \tan(v_{c_i} W_{ct} v_{c_i}^T + b_1) \tag{7}$$

Where v_{c_i} is the LCS vector, $f(\cdot)$ is the activation function, and b is the bias term. Next, the computation of MHA mechanism follows.

Inter-MHA involves the MHA computation between the context and aspect words. To address the issue of long dependencies, both the LCS and ATS are learned together. Inter-MHA is expressed as:

$$h_i = \mathrm{attention}(v_{c_i}, v_{a_j}) = \frac{\exp f(v_{c_i}, v_{a_j})}{\sum_{i=1}^{n} \exp f(v_{c_i}, v_{a_j})} v_{a_j} \tag{8}$$

$$f(v_{c_i}, v_{a_j}) = \tan([v_{c_i}, v_{a_j}] W_{at} + b_2) \tag{9}$$

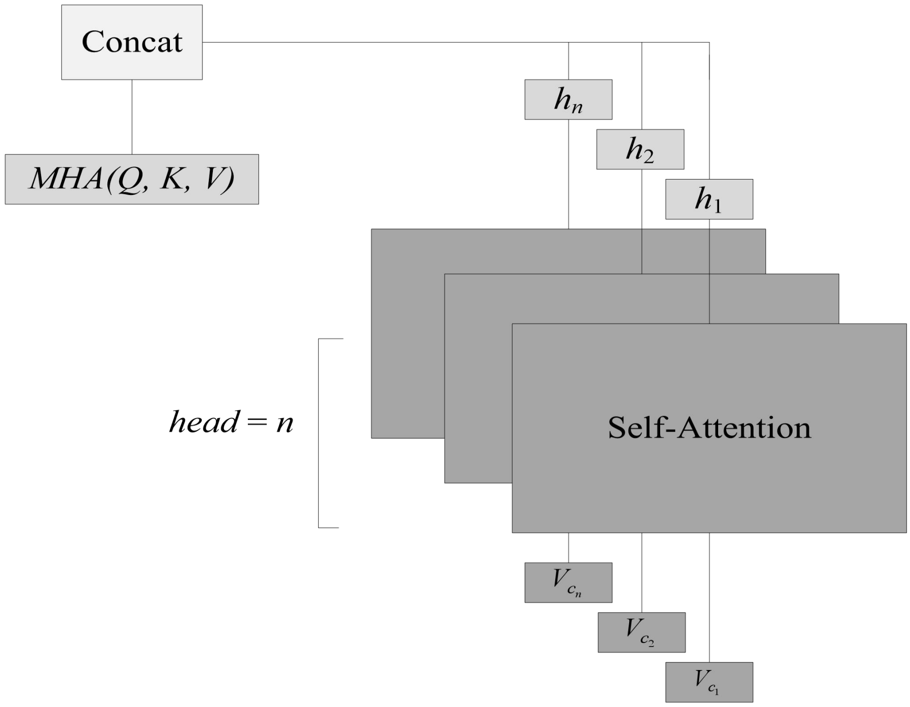

Figure 3. Structure of the Intra-MHA module.

Where v_{a_j} is the ATS vector, W_{at} denotes the trainable weight, and b is the bias value.

PCT transforms the features obtained by MHA to acquire the sequence relationships of the text. Point-wise convolution means that the convolution kernel is 1, applying the same convolution operation to each word in the input sequence. Assuming the input sequence is H, the PCT operation is defined as follows:

$$\mathrm{PCT}(H) = \sigma(H * W_1 + b_3) * W_2 + b_4 \tag{10}$$

where σ represents the activation function, $*$ denotes the convolution operation, W_1 and W_2 represent two learnable convolutional kernel parameters, while b_3 and b_4 represent bias parameters that need to be learned. After the PCT operation, the attention encoding layer produces hidden features h^c, h^a, and h^g for LCS, ATS, and GSS, respectively.

To strengthen the relationship between text and aspect, the AST module is employed for learning, along with residual structures to enhance information propagation. Aspect information is integrated into text representations to obtain specific aspect-level text features. Concatenating the GSS vector v_g with v_{c_i} and v_{a_j}, and passing through an activation function to increase non-linear representation capability:

$$\bar{v}_g = \sigma(W_g[v_g \oplus v_{c_i} \oplus v_{a_j}] + b_c) \tag{11}$$

To preserve contextual information, the strategy of information retention in residual networks is employed. The GSS vector $\bar{v}_g$ with integrated ATS and LCS information is added to the text feature vector v_g, resulting in the final feature with merged aspect information:

$$v = v_g + \bar{v}_g \tag{12}$$

3.3. **Feature extraction.** The SRD refers to the degree of semantic influence between two words within the same sentence. Generally, the closer the semantic distance between two words, the higher the degree of semantic relevance between them. SRD is generally categorized into two types: sequence distance and dependency distance [37]. Sequence distance refers to the absolute distance between the positions of two words in a sentence. Dependency distance refers to the shortest distance between the corresponding nodes of two words in the syntactic dependency tree. If the aspect term consists of multiple words, then SRD is calculated as the average distance between each component word of the aspect word and the input words:

$$SRD = (S_1^{dis} + S_2^{dis} + \cdots + S_i^{dis}) \times \frac{1}{i} \tag{13}$$

where $S_i^{dis} \in [1, L]$, S_i^{dis} represents the distance from the central word to the context word, and L is the length of the entire sentence.

Based on the computed SRD, a dynamic context masking mechanism is applied, where irrelevant words are masked to better avoid the influence of interfering words on sentiment polarity during feature extraction. LCFDM, centered on the aspect word, with SRD as the radius, only computes the next-step attention mechanism for words within the SRD distance on both sides of the aspect word. Masked irrelevant words do not participate in the next-step attention mechanism. The LCFDM mechanism blocks tokens that are further than SRD. The masked sequence obtained is then used for the next step of MHA calculation along with the aspect words input to this module. Features masked by the LCFDM mechanism are set to 0, while unmasked features are set to 1. The output vector after using the LCFDM mechanism is represented as follows:

$$V_i^m = \begin{cases} 0, & SRD < \alpha \\ 1, & SRD > \alpha \end{cases} \tag{14}$$

When there are i vectors, M is the mask matrix obtained after LCFDM processing:

$$M = [V_1^m, V_2^m, \ldots, V_i^m] \tag{15}$$

The mask matrix is multiplied with the local contextual matrix output to obtain the masked LCFDM vector.

By reducing the weights of irrelevant words, GCFDW diminishes the impact of irrelevant words on context feature extraction. Centered around aspect focal words and with SRD as the radius, GCFDW lowers the weights of words beyond SRD distance. The resulting vectors after employing the GCFDW mechanism are then utilized. The obtained new sequence, along with the aspect words inputted into this module, proceed to the next step of the MHA mechanism. GCFDW is expressed as:

$$V_i^w = \begin{cases} 1 - \frac{SRD_i - \alpha}{N}, & SRD > \alpha \\ 1, & SRD \leq \alpha \end{cases} \tag{16}$$

Where SRD_i represents the i-th SRD distance. When there are i vectors, W is the matrix obtained after GCFDW processing:

$$W = [V_1^m, V_2^m, \ldots, V_i^m] \tag{17}$$

The mask matrix is multiplied with the local contextual matrix output to obtain the masked GCFDW vector.

3.4. **Feature fusion and sentiment classification.** In the fusion of context, aspect and global features, conventional fusion methods such as linear layers, concatenation, addition, and multiplication tend to compromise and obscure feature information, ultimately leading to a decline in model performance. To address this issue, a new feature fusion structure is devised based on CLN, incorporating layer normalization (LN) to sequences while integrating additional conditions c_1 and c_2 into the LN process to enhance features

[38]. The computation processes of LN and CLN are as follows:

$$LN(x) = \frac{x - E[x]}{\sqrt{Var[x] + \epsilon}} * \phi + \eta \tag{18}$$

$$CLN(\psi, c_1, c_2) = \frac{\psi - E[\psi]}{\sqrt{Var[\psi] + \epsilon}} * W_\phi c_1 + W_\eta c_2 \tag{19}$$

where $E[x]$ denotes the mean of x, $Var[x]$ represents the variance of x. ϵ is a minimal constant to prevent the denominator from being zero, ϕ and η are scaling and shifting variables, respectively. W_ϕ and W_η stand as trainable parameters, and c_1 and c_2 denote the conditions awaiting fusion. In comparison to LN, CLN linearly transforms conditions c_1 and c_2 into two distinct spaces, incorporating them as scaling variable ϕ and shifting variable η into the normalization process of ψ.

The outputs of LCS, ATS, and GSS modules are concatenated into $t = \{t_1, t_2, \ldots, t_n\}$, and then fed into a softmax layer for sentiment classification. The final sentiment classification scores fall within $\{-1, 0, 1\}$, representing sentiment polarities $Y \in \{negative, neutral, positive\}$. The softmax classification can be expressed as follows:

$$Y = Softmax(t) = \frac{\exp(f(t))}{\sum_{x=1}^{3} \exp(f(t))} \tag{20}$$

4. **Experiment.** Firstly, the datasets utilized in the experiment, model parameter configurations, and evaluation metrics are introduced. Then, the proposed method is validated for conducting a fine-grained assessment of CPS quality.

4.1. **Dataset.** A vast collection of feedback texts related to CPS was gathered from various sources, including social media platforms, online forums, and review websites, to constitute the experimental dataset. This dataset encompasses diverse perspectives, opinions, and emotional experiences of community residents regarding various aspects of public services, reflecting the real-life situation concerning the quality, efficiency, and attitudes associated with public services. The dataset comprises evaluations of CPS from different angles. Some comments are single-attribute, such as "This is the best community doctor I've encountered, witty and patient," which evaluates service quality exclusively. Others contain multiple attributes, like "The volunteers are super enthusiastic, but sometimes the waiting time is a bit long; hoping for improvement," which includes both service attitude and efficiency attributes. The experimental dataset was divided into training, validation, and testing sets in a 7:2:1 ratio. Table 1 categorizes the textual objects of the comments based on various influencing factors of CPS into five aspect categories: service efficiency, service attitude, fairness, information transparency, and sustainability. Table 2 presents the statistical information of the experimental dataset.

4.2. **Parameter Settings and Evaluation Metrics.** Our experiments were conducted by fine-tuning the pre-trained model bert-uncased-base provided by the transformers library. This model was trained on an NVIDIA GeForce RTX 2080 Ti GPU with 12 GB graphic memory. During the fine-tuning of BERT, a very small learning rate is required. Therefore, the learning rate was set to 2×10^{-5}, while the hidden dimension and embedding dimension were set to 768. The dropout rate was set to 0.1, and L2 regularization was set to 1×10^{-5}. The batch size was set to 16. The Adam optimizer was employed to adapt to sparse gradients and alleviate the problem of gradient oscillation. A total of 10 epochs were trained.

Two subtasks were defined for each dataset in this paper: (1) Aspect Detection; (2) ABSA. For aspect detection, it identifies whether the input sentence mentions any aspect

Table 1. Aspect categorization of CPS

Aspect	Aspect terms	Description
Efficiency	Waiting time, Processing speed, Efficiency, Delay, Inefficiency	The speed and efficiency of handling affairs in CPS are assessed. Emphasis is placed on aspects such as waiting time, efficiency, and service speed when users conduct transactions or access services.
Attitude	Attitude, Friendliness, Rudeness, Unfriendliness	The service attitude and quality of staff in CPS are evaluated. Attention is mainly focused on the friendliness, professionalism, and enthusiasm of staff.
Fairness	Fairness, Equality, Equity, Bias, Discrimination	The fairness and equality of CPS are evaluated. The focus is primarily on the fairness of service to different groups, equal rights, and impartial service.
Transparency	Transparency, Policy disclosure, Information disclosure, Hidden information	The transparency and openness of information regarding CPS are assessed. The degree of openness and transparency of information such as policies, processes, and service regulations, as well as the transparency of information provided to residents, are mainly scrutinized.
Sustainability	Sustainability, Long-term benefit, Continuity, Unsustainability, Discontinuity	The ability and long-term benefits of sustainable development of CPS are evaluated. Emphasis is placed on the long-term benefits of service projects, stability of service models, and long-term impact on community development.

Table 2. Statistical information of the experiment dataset

Aspect	Negative	Positive	Neutral
Efficiency	560	329	135
Attitude	628	294	100
Fairness	588	358	130
Transparency	595	282	125
Sustainability	704	275	86
Total	**3075**	**1538**	**576**

categories from a predefined set of aspects. ABSA tasks involve analyzing the sentiment polarity of given aspects contained in sentences.

In aspect detection, precision, recall, and F1 score were utilized as performance metrics. Precision denotes the proportion of correctly predicted positive class samples among all samples predicted as positive. Recall represents the proportion of correctly predicted positive samples among all actual positive samples. F1 score is the harmonic mean of precision and recall.

$$Pre = \frac{TP}{TP + FP} \tag{21}$$

$$Re = \frac{TP}{TP + FN} \tag{22}$$

$$F_1 = \frac{2 \times Pre \times Re}{Pre + Re} \tag{23}$$

In ABSA tasks, accuracy is employed as the performance metric. Accuracy is the proportion of correctly predicted samples out of the total number of samples:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{24}$$

where TP represents the number of samples predicted as positive and actually positive, TN represents the number of samples predicted as negative and actually negative. FP represents the number of samples predicted as positive but actually negative, and FN represents the number of samples predicted as negative but actually positive.

4.3. **Experiment results.** In order to investigate the impact of different semantic relevance distances on the proposed model and to find the optimal SRD threshold parameter, experiments were conducted on the SRD threshold α, sequence distance, and dependency distance to evaluate the best semantic relevance distance and threshold under different circumstances for ABSA task. The results are shown in Figure 4, where sequence distance is denoted as SD and dependency distance as DD. From Figure 4, it is evident that using sequence distance outperforms using dependency distance. The optimal results for this experiment were achieved when the threshold was around 3.

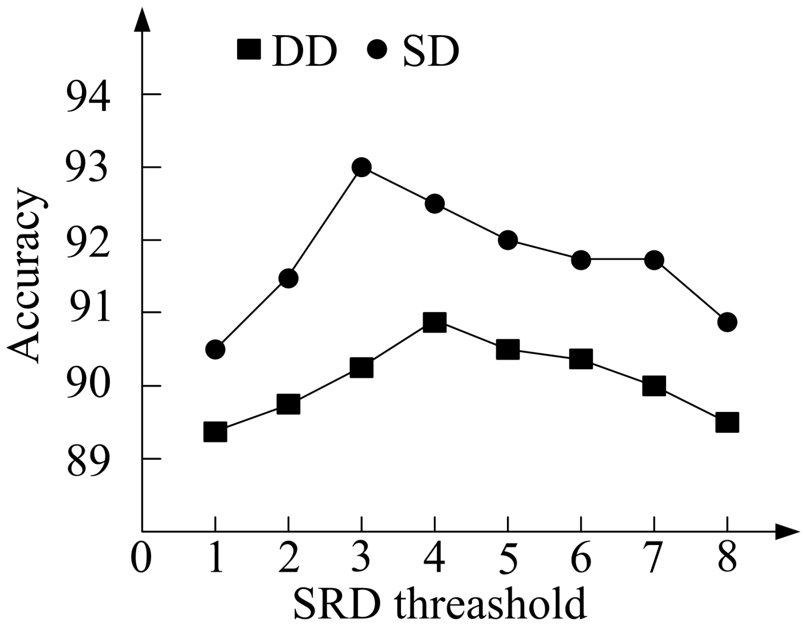

Figure 4. ABSA results with different semantic relevance distance and SRD thresholds.

Table 3 and Figure 5 respectively present the performance comparison of the proposed method with the comparison methods in the aspect detection and ABSA tasks on the experimental dataset.

Table 3. Experimental results of aspect detection (%)

Models	**Pre**	**Re**	**F1**
[18]	63.77	65.82	64.77
[21]	78.44	77.63	78.09
[29]	82.77	83.45	83.01
[30]	84.62	85.19	84.93
Proposed method	**88.34**	**89.62**	**89.05**

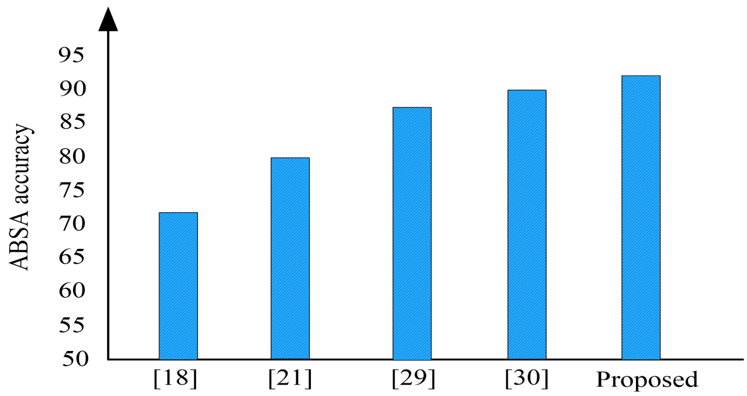

Figure 5. Comparison of ABSA accuracy.

In order to analyze the importance of each component of the proposed model, ablation experiments regarding aspect extraction and ABSA tasks were designed, and the experimental results are listed in Table 4.

Table 4. Ablation study results (/%)

LCS	**ATS**	**GSS**	**CLN**	**Aspect Detection**	**ABSA**
				F1	**Accuracy**
✓				83.28	89.57
✓	✓			85.37	90.42
✓	✓	✓		88.64	92.71
✓	✓	✓	✓	89.05	93.21

5. **Conclusion.** In this study, a method for evaluating the quality of CPS based on the BERT model and attention mechanism is proposed and empirically investigated. Through aspect-level analysis of public feedback texts, the quality of CPS has been successfully evaluated from five aspects: service efficiency, service attitude, fairness, information transparency, and sustainability. The proposed model combines the local context attention, aspect term attention and global sentence attention for feature extraction, enabling efficient extraction of sentiment features for specified aspect terms. Experimental results demonstrate that our approach can accurately assess the quality of various aspects of CPS and provide scientifically effective decision support for government departments and

relevant institutions. In future research, we will further explore how to optimize the performance of the model and apply it to a broader range of tasks for evaluating the quality of social public services.

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