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Breaking down linguistic complexities: A structured approach to aspect-based sentiment analysis

Kanwal Ahmed [a], Muhammad Imran Nadeem [a,*], Zhiyun Zheng [a,*], Dun Li [a], Inam Ullah [b], Muhammad Assam [c], Yazeed Yasin Ghadi [d], Heba G. Mohamed [e,*]

[a] School of Computer and Artificial Intelligence, Zhengzhou University, Zhengzhou 450001, China
[b] College of Information Engineering, Henan University of Technology, Zhengzhou 450001, China
[c] Department of Software Engineering, University of Science and Technology Bannu, KP, Pakistan
[d] Department of Computer Science, Al Ain University, United Arab Emirates
[e] Department of Electrical Engineering, College of Engineering, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia

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A B S T R A C T

Aspect-based sentiment analysis refers to the task of determining the sentiment polarity associated with particular aspects mentioned in a sentence or document. Previous studies have used attention-based neural network models to connect aspect terms with context words, but these models often perform poorly due to limited interaction between aspect terms and opinion words. Furthermore, these models typically focus only on explicitly stated aspect objects, which can be overly restrictive in certain scenarios. Current sentiment analysis methods that rely on aspect categories also often fail to consider the implicit placement of aspect-category information within the context. While existing models may produce strong results, they often lack domain knowledge. To address these issues, this study proposes an Aspect-position and Entity-oriented Knowledge Convolutional Graph (APEKCG) consisting of two modules: the Aspect position-aware module (APA) and the Entity oriented Knowledge Dependency Convolutional Graph (EKDCG). The APA module is designed to integrate aspect-specific sentiment features for sentiment classification by incorporating information about aspect categories into different parts of the context. The EKDCG module incorporates entity-oriented knowledge, dependency labels, and syntactic path using a dependence graph. Experimental results on five benchmarks Natural Language Processing (NLP) datasets of the English language demonstrate the effectiveness of the proposed APEKCG framework. Furthermore, the APEKCG outperformed previous state-of-the-art models with its accuracy, achieving 89.13%, 84.32%, 89.02%, 79.64%, and 90.22% on the MAMS, Laptop, Restaurant, AWARE, and SemEval-15&16 datasets, respectively.

1. Introduction

Aspect-based sentiment analysis (ABSA) (Zhu et al., 2023; Wu et al., 2022a; Zhang et al., 2022a) is a specialized area within text sentiment analysis (Li et al., 2022c; Zhao et al., 2021a) that aims to determine the sentiment polarities of users towards specific aspect terms in a sentence. ABSA is different from traditional sentiment analysis because it focuses on aspect terms rather than entire documents or sentences. This approach allows for better insight into user reviews as it captures the sentiment of each aspect separately. For example, in the sentence "Great food but the service was dreadful!", the aspect terms "food" and "service" have positive and negative sentiment polarities, respectively. Sentence-level or document-level sentiment analysis would not be able to accurately reflect this contrast in sentiment. Initially, ABSA relied on linguistic variables to train classifiers and conduct sentiment analysis on customer feedback using traditional machine learning techniques like Naive Bayes, Logistic Regression, and Support Vector Machine. These methods focused on

* Corresponding authors.
E-mail addresses: Kanwal_ahmed@gs.zzu.edu.cn (K. Ahmed), imran_nadeem@gs.zzu.edu.cn (M.I. Nadeem), iezyzheng@zzu.edu.cn (Z. Zheng), ielidun@zzu.edu.cn (D. Li), Yazeed.ghadi@aau.ac.ae (Y.Y. Ghadi), hegmohamed@pnu.edu.sa (H.G. Mohamed).

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high-frequency nouns or noun phrases that could indicate a reviewer's emotional stance. However, there were limitations to this approach, as some nouns were not sentiment items, and some exceptional aspects were rarely discussed. Recent research has explored neural networks like Convolution-based Networks (Nadeem et al., 2022), Long Short-Term Memory (LSTM) Networks, and Recurrent Neural Networks (RNN) (Nadeem et al., 2023), which consider a phrase as a sequence of words. However, these models had limitations in capturing long-term dependencies between words and preserving syntactic information.

Within the realm of ABSA, a clear differentiation exists between "aspect" and "attention." Specifically, an aspect corresponds to the precise constituents or characteristics that undergo scrutiny within the ABSA framework. Conversely, attention assumes the role of a computational mechanism employed in models to allocate varying degrees of significance or emphasis to distinct segments of the input sequence, which encompass the aspects under consideration. As researchers sought to address this matter, novel approaches such as Gated Convolutional Networks (Xue and Li, 2018) and Attention methods (Mao et al., 2019) were introduced. However, these approaches inadvertently neglected the incorporation of essential syntactic information (Wang et al., 2016; Huang and Carley, 2019). To rectify this limitation, the Aspect Position-Aware module (APA) was developed, aiming to accentuate the significance of aspect-category information at different positions within the context. Structured models play a critical role in sentiment analysis in natural language processing (NLP), with two major categories being tree-based models and graph neural networks (GNNs). Tree-based models, such as Tree-LSTM (Tai et al., 2015), use phrase or dependency trees to capture syntactic information, while GNNs, such as Attention Graph Convolutional Network (Wu et al., 2022a; Huang et al., 2020) GCN (Zhu et al., 2023; Zhang et al., 2019a), and Relational GCN (Liang et al., 2022) incorporate graph convolutional procedures to utilize both syntactic and semantic information. Both types of models have shown promise in sentiment analysis, particularly in ABSA, and have the potential to accurately represent data and detect complicated emotional polarities. While tree-based models may struggle with syntactic parsing issues (Jang et al., 2016; Li et al., 2021a), GNN models can provide stable and meaningful structures (Tang et al., 2020; Tian et al., 2021). Ultimately, the success of sentiment analysis relies on the incorporation of syntactic and semantic information through structured models. Recent advances in GNNs have enabled the capturing of neutral and ambivalent attitudes in comment data by aggregating information from node edges. However, these models ignore the dependence labels present on the edges, which can be useful for mining sentiment pairings, and do not consider domain knowledge that can influence sentiment polarity. Considering this, we present a unique Entity oriented Knowledge Dependency Convolutional Graph (EKDCG) for the ABSA challenge in this research.

To address the aforementioned issues the main objective of this research:

1. To propose a novel framework for aspect-based sentiment analysis, named the Aspect-position and Entity-oriented Knowledge Convolutional Graph (APEKCG). This framework aims to consider both explicitly stated aspect objects and the implicit placement of aspect-category information within the context.
2. To integrate domain knowledge into the APEKCG framework by incorporating entity-oriented knowledge, dependency labels, and syntactic paths. This integration of domain knowledge seeks to enhance the performance of aspect-based sentiment analysis.
3. To overcome the challenges encountered in aspect-based sentiment analysis by improving the interaction between aspect terms and opinion words, thereby mitigating the limitations observed in previous attention-based neural network models.

Our proposed APEKCG model consists of two modules: APA and EKDCG. The APA module converts sentence and aspect category words into vector representations, while the EKDCG module builds an entity-oriented knowledge graph using review information to capture positive and negative sentiment polarity. We then use a Relational Attention Graph Convolutional Network (RAGCN) to execute the ABSA task by combining nodes, edges, syntactic paths, and dependency labels on the edges. The output from both modules is combined and fed into the classifier for the final output. Our method improves the traditional methods of paying attention by using aspect-position embedding as the attention metric, resulting in a more accurate computation of attention weight.

Overall, the following are the main contributions of this paper:

1. The paper proposes a novel APA module that integrates aspect categories with contextual information for capturing the relationship between aspects and their context.
2. Additionally, a boosted attention network that uses aspect-position embedding representation is presented to enhance aspect-specific sentiment analysis by focusing on the position of the aspect in the sentence.
3. The paper also proposes integrating entity-oriented knowledge into the dependency tree of sentences and building EKDCG module to uncover latent sentiment polarity. The dependency graph network is modeled using the labels on the edges indicating dependencies, as well as domain knowledge and the syntax path. Together, the APA module and EKDCG offer a powerful approach to sentiment analysis that is both accurate and contextually aware.
4. We show that our APEKCG greatly outperforms the state-of-the-art algorithms on the ABSA problem by analyzing experimental findings on the benchmark datasets.

This article's remaining content is structured as follows. In Section 2, we examine the prior research that paved the way for our approach. In Section 3, a detailed framework of our proposed model APEKCG has been presented. Section 4 includes datasets, implementation details, and analysis of results. The final section of the paper summarizes our efforts and offers a look ahead at potential future lines of the research.

2. Literature review

In light of the proliferation of online discourse, sentiment analysis is gaining traction in both academic and commercial settings (Hoang et al., 2019). As one of the subtasks of sentiment analysis, ABSA has gained significant attention in recent years. ABSA involves identifying both sentiments and aspects in a highly complex task. In recent research, attention mechanisms have been integrated into neural networks to capture the combination of aspects and emotions in text phrases (Wang et al., 2016Tang et al., 2015; Chen et al., 2017). For instance, to isolate crucial feelings about the focus area, Wang et al. (2016) presented an attention-based LSTM. Similarly, Nguyen and Le Nguyen (2018) recorded each context word in reference to a specific target by using a typical attention-based LSTM to model semantic linkages between each context word and a target. To solve the ABSA challenge, Tang et al. (2016) created a memory network that uses multi-hop attention and external memory, while Chen et al. (2017) developed a multilayered technique for capturing the polarity of a sentiment item over time. In the field of sentiment analysis across multiple domains, Co-LSTM, a CNN-LSTM hybrid model proposed by Behera et al. (2021), requires extensive training on diverse data, limiting its practicality. Li et al. (2022a) analyzed emotions in online reviews using social cognitive theory and the Intent-Indicator sentiment lexicon. These approaches, as well as others (Ma et al., 2017; Fan et al., 2018), successfully extract syntactic structure implicitly through the application of attention mechanisms, presenting a novel concept for the ABSA task (Nassif et al., 2021; Lin et al., 2020). It has been observed that sentiment words and items are often located in close proximity, indicating the effectiveness and efficiency of mining syntactic structure through attention mechanisms. Additionally, these approaches have the potential to overcome the problems of long word dependencies and gradient disappearance or explosion that are encountered by RNN-based models. In some studies, language models like BERT have been utilized to collect aspect-sentiment pair data to improve the way languages are represented and make ABSA more accurate (Hoang et al., 2019; Li et al., 2019).

For the task of ABSA, BERT, GPT, and RoBERTa can all be viable options for generating contextualized word embeddings. However, BERT is often considered a strong choice for ABSA due to its specific design and performance characteristics. As BERT's bidirectional architecture allows it to consider both the left and right contexts of a word, capturing a comprehensive understanding of word meanings and relationships. This is beneficial for ABSA, where the sentiment of an aspect often depends on the surrounding context. Additionally, it has the ability to capture fine-grained contextual information helps in recognizing the sentiment associated with different aspects. While GPT and RoBERTa are powerful models, they have different focuses. GPT is more suited for autoregressive language modeling and text generation, while RoBERTa is an optimized variant of BERT that improves performance but doesn't have specific design features tailored for ABSA (Zhou et al., 2021).

Catching aspect-emotion pairs through attention processes is insufficient when the aspect and emotion terms in a comment are far apart. While the attention mechanism is crucial in earlier neural models, it is insufficient. To address this constraint, researchers have suggested leveraging syntactic details to identify aspect-sentiment pairs and word dependency relationships. One proposed solution is the target-dependent graph attention network (TD-GAT) developed by Huang and Carley (2019), which classifies sentiment at the aspect level using dependency graphs. Another approach by Zhang et al. (2019b) is the proximity-weighted convolutional network, which considers the syntax of each aspect to represent contexts more accurately.

GNNs that leverage dependency information have been found to be highly effective in capturing aspect-sentiment pairs, as supported by empirical evidence that shows significant improvements in accuracy for the ABSA test (Hou et al., 2019; Wang et al., 2018). A recent study proposed a novel Graph Convolutional Network called AAGCN, which integrates attention to aspects. The authors modified the original sentence's syntactic dependency tree, using a beta distribution-based algorithm that takes into account both the aspect and external emotional knowledge to figure out the relationship weights between the two (Liang et al., 2023). This allows the AAGCN to effectively capture the sentiment expressed towards specific aspects of text data, improving the overall performance of sentiment analysis tasks.

GCN networks have been developed to classify emotions across various dimensions. In a subsequent study, researchers proposed a novel meta-learning technique that considers both historical and real-time aspect-aware data for a new few-shot aspect category sentiment analysis task (Liang et al., 2021). In addition, some studies have combined syntactic data with common sense knowledge in GCNs. For example, the SEDC-fusion GCNs leverage syntactic knowledge (Zhu et al., 2022), while Syntactic-GCN employs semantic knowledge (Dai et al., 2022), BiERU uses the bidirectional emotional recurrent unit (Li et al., 2022b), and SenticGCN integrates sentiment knowledge (Liang et al., 2022). Zhao et al. (2021b) suggested a syntax memory model that can encode syntactic dependency edges and label information together. Jain et al. (2022) combined the TF-IDF technique with a Binary Brain Storm Optimization algorithm for detecting aspects. Zhu et al. (2023) proposed KMGCN, a knowledge-guided multi-granularity graph convolutional neural network with a multi-granularity attention mechanism that enhances the interaction between aspect terms and opinion words. SSENM, proposed by Xiang et al. (2022), is a semantic and syntactic-enhanced neural model that includes dependency graphs and a self-attentive mechanism to capture semantic contextual information. The topic of affective computing and sentiment analysis has attracted the attention of many researchers due to the essential role it will play in the development of emotionally intelligent products. The field of study is interdisciplinary, spanning across Computer Science Cognitive Science, and Psychology (Cambria et al., 2017). In affective computing and sentiment analysis, the main areas of research are computation (Zhang et al., 2022b), interpretation (Cambria et al., 2022), or neurosymbolic AI, like SenticNet 7 (Han et al., 2019; Cambria et al., 2019), and the generation (Liu et al., 2020) of human emotions or moods.

Luo et al. (2020) presented a novel approach named GRACE (Graph-Attentive Cascaded Labeling) for ABSA. GRACE employs a cascaded labeling strategy to foster improved interaction between aspect terms and enhance the attention allocated to sentiment tokens during the sentiment polarity labeling process. The model incorporates two decoder modules: one for aspect term extraction (ATE) and another for aspect sentiment classification (ASC). In the ASC module, GRACE leverages a stacked multi-head attention mechanism to capture the interplay between aspect terms. Furthermore, to tackle the challenge posed by imbalanced labels, the model employs a gradient harmonized loss function. Karimi et al. (2020) presented novel advancements tailored for ABSA tasks, specifically focusing on enhancing the BERT model. The authors proposed two additional modules, namely parallel aggregation and hierarchical aggregation, to augment the capabilities of BERT for ABSA. Ben Veyseh et al. (2020) presented a methodology termed GGCN (Graph-based Global Context Network) along with syntax-based regulation to enhance ABSA. The proposed approach integrates multiple fundamental components, including representation learning (RL), graph convolution and regulation (GCR), as well as syntax and model consistency (SMC).

Liang et al. (2021) proposed an interactive architecture consisting of five layers, augmented with a multi-task learning framework, specifically designed for the ABSA task. This proposed architecture enables effective interaction and information flow between the different layers, facilitating the integration of multiple tasks within the ABSA framework. Zhang et al. (2021) introduced the SSN (Syntactic-Semantic Network) model for aspect-level sentiment classification. Their research introduces a fusion mechanism that efficiently integrates aspect and context information, enabling a comprehensive understanding of sentiment at the aspect level. Qi et al. (2022) presented a model for aspect term sentiment classification that leverages aspect-sensitive word representations obtained via a weakly supervised approach. This methodology effectively tackles the issue of words exhibiting varying sentiment polarities based on different aspects, ensuring accurate sentiment classification at the aspect term level. Table 1 and Table 2 provide a concise overview of the relevant techniques, encompassing their respective contributions and limitations. It serves as a summary of the aforementioned approaches, allowing for a comprehensive understanding of the field.

Yu and Zhang (2023) present the multiweight graph convolutional network (MWGCN), aimed at addressing certain limitations

Table 1
Summary of literature review-1.

Model	Year	Dataset	Contributions	Limitations
GRACE (Luo et al., 2020)	2020	Rest14, Lap14, Rest15, Rest16, Twitter	This study effectively tackles the challenge of imbalanced labels and promotes interplay between aspects during the process of labeling polarities. It also facilitates meaningful interactions between different aspects, resulting in improved sentiment polarity labeling.	Post-training is an essential step in the process and necessitates the utilization of multiple loss functions.
Parallel and Hierarchical Aggregation (Karimi et al., 2020)	2020	Rest14, Lap14, Rest16	The incorporation of integration enhances the performance of BERT by mitigating overfitting challenges encountered when dealing with small datasets.	To address the overfitting issue associated with small datasets, a greater number of epochs is required. However, the inclusion of two distinct loss functions for separate tasks can impose a burden on the overall architecture, thereby resulting in inaccurate predictions.
GGCN (Ben Veyseh et al., 2020)	2020	Rest14, Lap14, MAMS	In this research, a customization approach was employed to modify the aspect terms at various hidden layers of Graph Convolutional Networks (GCN) for aspect term extraction. Furthermore, this study explicitly leverages the global importance scores of words in the sentence to capture the syntactic neighbor words, thereby enhancing the syntactic analysis aspect of the model.	By minimizing the cosine similarities between the gate vectors, this approach inadvertently generates irrelevant outcomes. Furthermore, the model is solely designed to handle the Aspect Term Extraction (ATE) task without encompassing other tasks.
Position Bias (Ma et al., 2021)	2021	Rest14, Lap14	This study demonstrates robust aspect classification performance, even in Out-of-Domain (OOD) scenarios. It effectively addresses the challenges posed by adversarial perturbations in the input, ensuring reliable and accurate classification results.	This study is incompatible with pre-trained language models, as it lacks the ability to effectively extract the syntactic structure of the sentence.
DREGCN (Liang et al., 2021)	2021	Rest14, Lap14, Rest15	This study successfully captures the syntactic structure of the sentence by effectively leveraging multiple related tasks. It goes beyond the sentence-level analysis and incorporates document-level knowledge at the relational level, leading to a comprehensive understanding of the text.	This study encountered limitations in capturing the relationship between an aspect and a sentence when they are not in close proximity to each other.
SA-GCN (Hou et al., 2021)	2021	Lap14, Rest 14, Rest 15, Rest 16	This study effectively establishes the relationship between an aspect and opinion words, even in cases where they are spatially distant from each other within the sentence.	Expanding the number of GCN layers during training does not yield improvements in performance.

Table 2
Summary of literature review-2.

Model	Year	Dataset	Contributions	Limitations
SSN (Zhang et al., 2021)	2021	Restaurant, Laptop	This study emphasizes the significance of syntax and employing a fusion mechanism to seamlessly integrate aspect and context information.	In the Laptop experiment, the proposed model exhibits subpar performance in the case of three aspects. The research findings suggest that the model's inaccurate predictions are primarily concentrated on data instances where the aspect term spans more than four words.
R-GAT (Wu et al., 2022b)	2022	Rest14, Lap14, Twitter	This study concentrates on target aspects within the dependency tree to encode dependency relations, thereby establishing a strong correlation between aspects and targets.	This study encountered limitations in capturing relations within complex sentences. Specifically, it struggled to capture relations when the dependency distance between aspect and sentence words became excessively long.
ASWR (Qi et al., 2022)	2022	Restaurant-14, Laptop-14, Restaurant-15	The study emphasizes the significance of accounting for the aspect-specific characteristics of words in sentiment classification.	The proposed method utilizes weakly supervised techniques to construct aspect-sensitive lexicons, which may introduce certain inaccuracies when capturing the sentiments associated with specific aspects.

associated with the attention mechanism in detecting aspect-relevant semantics and incorporating aspect position information, specifically the limited detection of such semantics and the oversight of the aspect's long-distance dependence. The MWGCN method incorporates two weighting techniques, namely multi-grain dot-product weighting (MGDW) and Local Context weighted adjacency Graph (LCG). MGDW serves to preserve the overall context semantics while placing greater emphasis on aspect-related features. Ma et al. (2023) involves the development of the MultiGCN model, the introduction of difference and similarity losses, and the demonstration of improved prediction performance compared to existing models. Arumugam and Nallaperumal (2023) address the issue of long-range dependencies and the identification of sensitive and important words are tackled through the introduction of two separate methods. The first method, known as Adaptive Aspect-Specific GCN (AASGCN), enhances the Aspect-Specific Graph Convolutional Networks (ASGCN) by integrating adaptive weights. This enhancement enables more effective modeling of aspect-specific information. The second method, Emotional Intensive Sentiment Reasoning (EISR), incorporates emotionally intensive information into the reasoning mechanism. Moreover, the significance of commonsense knowledge, semantic understanding, and syntax information in ABSA has been recognized in previous research, yet few approaches have addressed them simultaneously. In response, a novel graph convolutional network is proposed that incorporates commonsense knowledge, syntax, and semantics (Zhao et al., 2023a). Wu et al. (2023) introduces the Aspect Word and Context Order Prediction Task (ACOP) as an auxiliary task. The ACOP task is implemented using both global and local context information for aspect-based sentiment analysis, and a self-supervised method is employed to train the model.

Zhao et al. (2023b) introduced a multitask learning framework for aspect-based sentiment analysis, which integrates Aspect Term Extraction (ATE) and Aspect Polarity Classification (APC) tasks. By training ATE as an auxiliary task, the model enhances the attention of APC on pertinent aspects, leading to improved aspect polarity classification. The inclusion of graph neural networks (GNN) and dependency syntax information significantly contributes to the enhanced performance of APC. Furthermore, the utilization of multihead attention (MHA) facilitates the association of dependency sequences with aspect extraction, effectively highlighting crucial dependency relations. The SA-BERT model, proposed by Mewada and Dewang (2023), leverages a combination of synthetic attention and bidirectional encoder representations from transformers to perform sentiment polarity classification on review datasets. By employing dynamic word vector encodings and transformers, the model adeptly captures the aspect and context of reviews, effectively representing their semantics. The synthetic attention mechanism employed by the model enables it to learn and focus on the essential components of context and aspects within the reviews. The MAPA BiLSTM-BERT model proposed by Wankhade et al. (2023), tackles unresolved challenges in aspect-level sentiment categorization. By integrating multiple aspect-specific position attention and aspect-specific attention mechanisms, the model effectively captures contextual information and handles multiple aspects simultaneously. Zheng et al. (2023a) proposed a Lightweight Multilayer Interactive Attention Network (LMIAN) for ABSA. LMIAN utilizes a pre-trained language model for initializing word embedding vectors. LMIAN incorporates an interactive computational layer that establishes correlations between aspect words and their contexts. These correlations are calculated through multiple computational layers using neural attention models. Xin et al. (2023) proposed a syntactic and semantic enhanced multi-layer graph attention network (SSEMGAT) that addresses the limitations of the dependency tree-based model by incorporating constituent trees and aspect-aware attention. SSEMGAT demonstrates competitive performance in sentiment analysis tasks, as evidenced by the evaluation of different datasets.

Zheng et al. (2023b) propose the design of a corpus-level sentiment knowledge fusion mechanism that enhances the understanding of sentiment information in aspect-based sentiment analysis. The use of dependency graphs, sentiment knowledge nodes, and shared sentiment knowledge leads to improved aspect representation and performance. Yang et al. (2023) combines adversarial training with the BERT model and capsule networks for aspect-based sentiment analysis. This integration allows for better utilization of neural networks' superiority and addresses the problem of insufficiently mining sentence semantic information due to limited training data. Zhang et al. (2023) introduce a Contrastive Learning Framework with Tree-Structured LSTM (CLF-TrLSTM). This framework leverages concatenated Tree-LSTMs and self-attention with a window mechanism to adeptly capture both syntactic and contextual information from dependency trees. Furthermore, it promotes alignment between anchor sentences and positive samples while effectively distinguishing them from negative example pairs. Table 3, Table 4, and Table 5 are provided to summarize the latest techniques, highlighting their respective contributions and limitations. This tabulated presentation offers a comprehensive overview of the recent advancements in the field.

Recent research indicates that achieving accurate sentiment analysis in ABSA tasks requires the incorporation of both linguistic and sentiment knowledge. In this study, the proposed APEKCG model uses aspect position attention and entity-oriented knowledge dependency graphs to conduct sentiment analysis. The model integrates multiple types of information, including aspect position attention, node and edge information, dependency label information on edges, entity-oriented knowledge, dependency labels, and syntax path, using ARGCN. Through Ablation Studies, the APEKCG model was shown to outperform current state-of-the-art models. Therefore, this study emphasizes the significance of incorporating entity-oriented knowledge and dependency labels in ABSA tasks and demonstrates the effectiveness of the APEKCG model in achieving accurate sentiment analysis.

3. Methodology

Our proposed methodology consists of two modules, named APA and EKDGC. Fig. 1 depicts the entire framework of the suggested methodology. Semantic representation, aspect-position embedding, and aspect-position attention learning make up the APA module. Aspect-specific sentiment information in sentences can be more smoothly integrated by using a strategy based on attention modeling in conjunction with aspect-position embedding. The APA modules successfully extract the necessary features, leading to reduced coupling and high robustness. In the second module EKDGC of the proposed framework APEKCG, we built an Entity-Oriented knowledge dependency convolutional graph in three phases according to K-Bert (Liu et al., 2020). As shown in Fig. 1 ("Knowledge Layer,") the process begins by building a knowledge graph of words that appear together in comment phrases. Second, the Biaffine parser (Dozat and Manning, 2016) and Stanford CoreNLP (De Marneffe and Manning, 2008; Manning et al., 2014) construct the dependency tree of the comment phrases, the structure of which is depicted in Fig. 1 ("Dependency tree"). Knowledge was fused into the dependency tree via the knowledge graph built with the help of the preceding processes, creating the Entity-Oriented knowledge dependency graph. Finally, we combine the entity-oriented knowledge dependency graph with the Attention Relational Graph Convolutional Network to synthesize the data from the nodes, edges, dependency labels, and domain expertise. The output generated from module 1 and module 2 is fused together and the final classifier generates the output, also described in Algorithm 1.

Algorithm 1. APEKCG

Input: *List of sentences, List of comment phrases*
Output: Final classification output

```
Module 1: features = Apply the APA Module on the list of sentences:
semanticReps = SemanticRepresentation(sentences)
aspectEmbeddedSentences = EmbedAspectPositions(semanticReps)
aspectSentencesWithAttention = AspectPositionAttention(aspectEmbeddedSentences)
features = ExtractFeatures(aspectSentencesWithAttention)
Module 2: graph = Apply the Entity-Oriented Knowledge Dependency Graph Convolutional (EKDGC) Module on the list of comment phrases:
knowledgeGraph = BuildKnowledgeGraph(commentPhrases)
dependencyTree = ConstructDependencyTree(commentPhrases)
entityGraph = FuseKnowledge(knowledgeGraph, dependencyTree)
synthesizedData = SynthesizeData(entityGraph)
fusedOutput = Combine(features, synthesizedData)
finalOutput = FinalClassifier(fusedOutput)
Return finalOutput
```

3.1. Module 1: Aspect Position-aware Module (APA)

This section is further divided into subsections which are described in detail.

Table 3
Summary of most recent literature review-1.

Model	Year	Dataset	Contributions	Limitations
MultiWeight Graph Convolutional Network (MWGCN) (Yu and Zhang, 2023)	2023	Twitter, Lap14, Rest14, Rest15, Rest16	By combining context representations, syntactic information, and aspect features using the weighted adjacency graph, the multilayer GCN focuses on local context information for improved ABSA performance.	The study acknowledges that selecting coefficients manually through experiments to optimize the model is inefficient. Therefore, the study suggests the need to explore the adaptive selection of coefficients in the ABSA model in order to ensure optimal model performance.
MultiGCN (Ma et al., 2023)	2023	Restaurant, Laptop, Twitter, MAMS	The study finds that models utilizing a dependency tree or its variants tend to achieve higher accuracy rates in aspect-based sentiment analysis (ABSA), indicating the benefits of incorporating structural information.	The study does not explicitly address the impact of the observed dependency labels on different types of sentiments or specific aspects. Furthermore, the study does not explore the generalizability of the findings to languages other than English.
EIAASG (Arumugam and Nallaperumal, 2023)	2023	REST16, REST15, REST14, LAP14, TWITTER 17	The study introduces two approaches, the first approach, AASGCN, enhances ASGCN by incorporating adaptive weights, enabling better capture of the semantic meaning of opinion targets. The second approach, EISR, incorporates emotionally intensive information into the sentiment analysis mechanism.	The study lacks a comprehensive discussion of the limitations or potential challenges associated with the proposed enhancements. Addressing these limitations could provide a more nuanced understanding of the performance and applicability of the proposed models.
SSK-GCN + BERT (Zhao et al., 2023a)	2023	Twitter, Lap14, Rest14, Rest15, Rest16	By combining knowledge, syntax, and semantics, the proposed model achieves improved performance in sentiment prediction.	One limitation of the study is that it does not consider edge information, which could be a potential avenue for further improvement in future research.
ACOP (Wu et al., 2023)	2023	Restaurant, Laptop, Twitter	The contributions of this study involve the introduction of a multi-task approach for ABSA, and the implementation of the ACOP learning strategy for sentence semantics in ABSA.	The limitations of this study include the lack of integration of external knowledge, the noise introduced in the local approach, and the need for further improvements and exploration of alternative techniques.
Syntax based (Zhao et al., 2023b)	2023	Restaurant, Laptop, Twitter	Incorporating GNN and dependency syntax information contributes to the performance of APC. The use of multihead attention (MHA) associates the dependency sequences with aspect extraction, emphasizing important dependency relations.	The proposed model may still face challenges in handling complex sentence structures or ambiguous aspect terms. The limitations and potential drawbacks of using multitask learning and the specific approaches employed in the study are not thoroughly discussed.

Table 4
Summary of most recent literature review-2.

Model	Year	Dataset	Contributions	Limitations
SA-BERT (Mewada and Dewang, 2023)	2022	Laptop, Restaurant14, Restaurant 15, Restaurant 16	The proposed SA-BERT model, combines synthetic attention with bidirectional encoder representations from transformers, which achieves high accuracy and F1 scores in classifying sentiment polarity in review datasets.	The assessment of sentence dependency relationships has not been conducted in the presented study.
MAPA BiLSTM BERT (attention based) (Wankhade et al., 2023)	2023	laptop, restaurant, Twitter	The proposed model considers multiple aspects simultaneously, effectively reduces interference between different aspects, and directs attention to specific parts of the sentence.	One of the limitations of the study lies in the heightened complexity associated with assigning weights in various challenging scenarios, which is comparatively more challenging than previous approaches that do not incorporate syntax. Furthermore, this model introduces greater computational complexity compared to earlier methods.
LMIAN (Zheng et al., 2023a)	2023	Laptop, Restaurant, Notebook, Phone, Car, Camera	The LMIAN overcomes a shallow interactive approach, which results in a lack of complex sentiment information.	The limitations of the LMIAN model include potential struggles in capturing implicit sentiment, limitations in understanding complex information, and the need for additional modalities to improve judgment in certain cases.
SSEMGAT (Xin et al., 2023)	2023	Restaurant, Laptop, Twitter	The SSEMGAT model addresses noise in dependent trees and enhances syntactic and semantic features.	The limitations and potential challenges associated with dependent trees, composition tree structures, multi-head attention mechanisms, and deeper correlation between syntax and semantics are not explicitly outlined. Further investigation is required to explore these limitations and refine the model's design and performance.
SEGCN-BERT (Zheng et al., 2023b)	2023	Lap14, Rest14, Rest15, Rest16	The incorporation of a sentiment knowledge fusion mechanism at the corpus level enhances the comprehension of sentiment information in aspect-based sentiment analysis. By leveraging dependency graphs, sentiment knowledge nodes, and shared sentiment knowledge, the approach facilitates enhanced aspect representation and performance.	The limitations of the proposed model include its performance on knowledge-limited datasets, the limited impact of sentiment knowledge nodes on datasets with few opinion words, the inability to establish connections for phrase-level sentiment expressions, and the lack of specific guidance for addressing these limitations in future research.

3.1.1. Semantic representation

The essential task here is to identify and isolate the words in the original text that belong to the aspect categories. Our complete modeling architecture relies on the outcomes of the pre-trained BERT model to obtain the embedding representations of the text. WordPiece, a tool developed by BERT, is a tokenizer that can break down the input text X into a list of tokens. Next, a high-dimensional embedding representation is built from the token sequence as Eq. 1.

$$E_x = [e_c, e_1, e_2, \dots, e_n, e_s] \tag{1}$$

Table 5
Summary of most recent literature review-3.

Model	Year	Dataset	Contributions	Limitations
ABCN (Yang et al., 2023)	2023	Restaurant, Laptop, Twitter	The proposed ABCN approach combines the strengths of adversarial BERT, capsule networks, and label smoothing regularization to improve aspect-based sentiment analysis.	Limited analysis of adversarial training, Lack of extensive evaluation of different datasets, Evaluation of computational efficiency, and Lack of comparison with alternative approaches.
CLF-TrLSTM +Bert (Zhang et al., 2023)	2023	Restaurant, Laptop, Twitter	The integration of tree-LSTM for modeling syntactic information and self-attention with a window mechanism for capturing contextual information significantly enhances the framework's capability to leverage intrinsic information within sentences.	The proposed architecture necessitates the inclusion of all aspects present in the text as input, which can pose challenges in scenarios with a large number of aspects or when the aspects dynamically change. Moreover, the adoption of dependency trees and distinct encoders for syntax and context information may introduce additional complexity and computational overhead to the model.

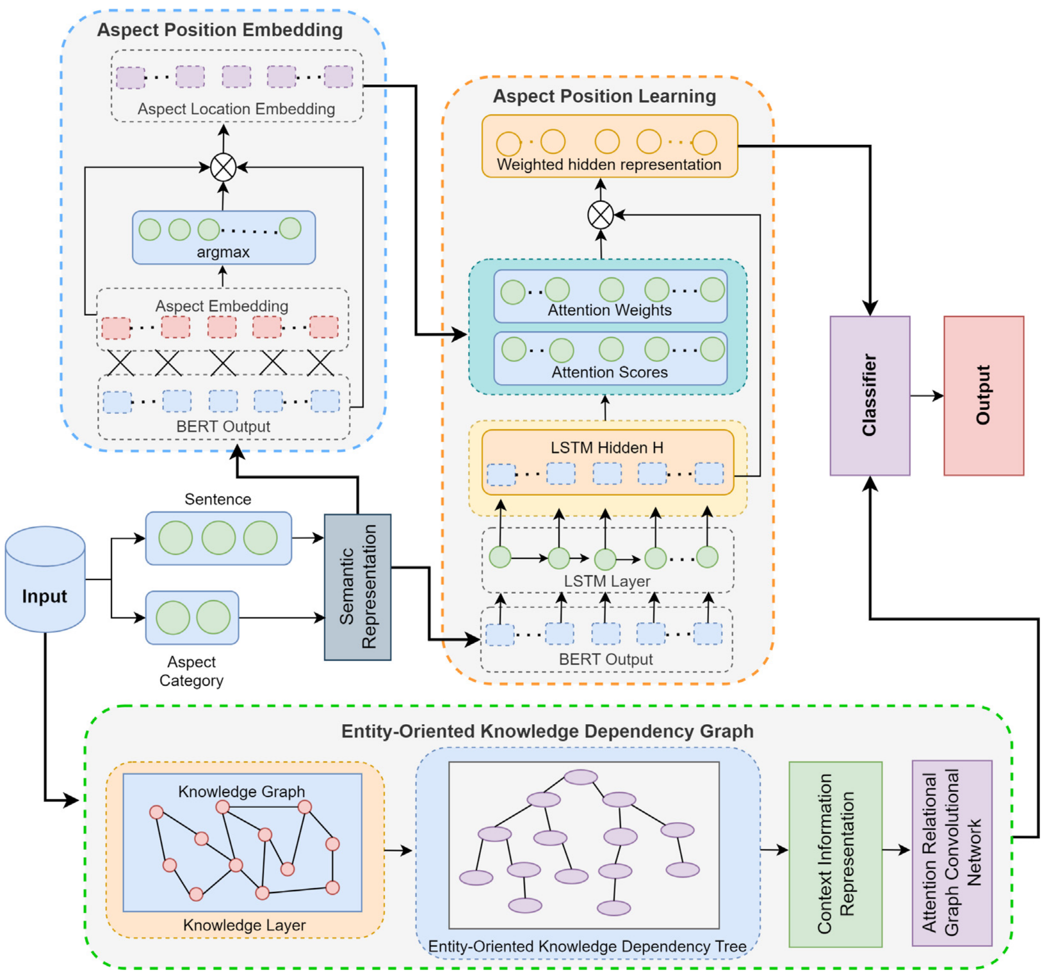

Fig. 1. Framework of the proposed methodology.

by use of the embedding layer. BERT's embedding layer has a dimension of d, so $E_x \in \mathbb{R}^{d\times(n+2)}$, where the length of the given text input is denoted by n. The CLS is represented by the vector (e_c) for the first token and the SEP by the vector (e_s) for the last token. Following the BERT multi-layer encoding, an initial embedding matrix is constructed using the hidden states of the last layer as Eq. 2.

$$T = [t_c, t_1, t_2, \ldots, t_n, t_s] \tag{2}$$

Given that $t_i \in \mathbb{R}^d$ provides the final properties of each token, it is abundantly evident that BERT has harmonious input and output dimensions. After taking this additional step, we will be able to obtain the embedding vector $v_a \in \mathbb{R}^d$ of the aspect category by transforming the aspect category terms into a preliminary embedding matrix T_a and then performing an average-pool operation on them as Eq. 3 and Eq. 4.

$$T_a = [t_c^a, t_1^a, t_2^a, \ldots\ldots, t_m^a, t_s^a] \tag{3}$$

$$v_a = \frac{1}{m+2}\left(t_c^a + t_s^a + \sum_{i=1}^{m} t_i^a\right) \tag{4}$$

3.1.2. Aspect-position embedding

This component is used to extract spatial references from text using the aspect category. The module's structure for embedding aspect and location information is shown in Fig. 1. The output of the text semantic representation module (i.e., the matrix T representing the final text embedding) and the obtained aspect-category embedding (v_a) serve as inputs to this section. While a given text may contain elements from numerous aspect categories, traditional BERT is unable to communicate the resulting richness of meaning. This method fails to clearly forecast the sentiment classification of different aspect categories, reverting to the text's sentiment classification. To make the original semantic representation more suitable for the supplied aspect category, We propose matching position information and creating an aspect-position embedding function to produce location features. This will allow us to construct location features. To be more specific, a similarity score is computed for the aspect-category vector v_a as well as for each vector contained in the vector–matrix T, and the index S_{max} of the vector that exhibits the greatest degree of similarity is selected as Eq. 5. After that, one calculates the embedding weight r_i of each vector in the matrix T by using Eq. 6:

$$S_{max} = argmax(v_a^T T) \tag{5}$$

$$r_i = \exp\left(-\frac{(i - S_{max})^2}{2\sigma^2}\right) \tag{6}$$

In the given context, the notation $i \in \{0, 1, 2, \ldots, n\}$ is the index of a word in the input text, and v_a^T is the transpose of matrix v_a. The hyperparameter $\sigma \in \mathbb{R}$ can be used to modify the rate at which a location is embedded. We can estimate the aspect-category distribution in the text by utilizing the similarity score, and our proposed aspect-position function's weights can prioritize crucial features closer to the aspect category while de-emphasizing features that are farther away. This accomplishes the effect of dynamically integrating information about aspect categories into text. We further enhance the location attributes' suitability for aspect categories by learning an aspect position representation from text and aspect-category embedding P. Mathematically, P can be determined by Eq. 10.

$$t_i^* = r_i \times t_i \tag{7}$$

$$v_a^i = (1 - r_i) \times v_a \tag{8}$$

$$p_i = t_i^* + v_a^i \tag{9}$$

$$P = [p_0, p_1, p_2, \ldots, p_n, p_{n+1}] \tag{10}$$

where $p_i \in \mathbb{R}^d$ represents the *ith* vector in the representation of aspect-position P.

3.1.3. Attention-to-aspect-position

Utilizing the attention mechanism, the module's primary role is to assimilate the text's most important details. The aspect-position attention learning module is shown by a schematic in Fig. 1. The text embedding matrix T and the aspect-position embedding P serve as the module's input units. The standard LSTM is not adept at focusing on capturing the essential semantic information that is linked to the aspect category in the text. As a solution, we augment the LSTM with a P-based attention technique based on aspect-position embedding. After feeding the text embedding matrix T into an LSTM, we obtained a series of hidden layer vector matrices H, where h_i is the hidden vector as Eq. 17, multiplied by a constant.

$$f_i = sigmoid(W_f.[h_{i-1}, n_i] + b_f) \tag{11}$$

$$g_i = sigmoid(W_g.[h_{i-1}, n_i] + b_g) \tag{12}$$

$$\widetilde{c}_i = tanh(W_c.[h_{i-1}, n_i] + b_c) \tag{13}$$

$$c_i = g_i \times \widetilde{c}_i + f_i \times c_{i-1} \tag{14}$$

$$o_i = sigmoid(W_o.[h_{i-1}, n_i] + b_o) \tag{15}$$

$$h_i = o_i \times \tanh(c_i) \tag{16}$$

$$H = [h_0, h_1, h_2, \ldots, h_{n+1}] \tag{17}$$

To which the weight matrices W_f, W_g, W_c, and $W_o correspond$, and the biases b_f, b_g, b_c, and b_o. Using the hidden vector sequence H, we may deduce how the aspect-position embedding matrix P relates to each hidden state. Using a weighted hidden representation $v_\alpha \epsilon \mathbb{R}^d$, the attention-weight vector $\alpha \epsilon \mathbb{R}^{n+2}$ is created using the aspect-position attention mechanism as Eq. 19 and Eq. 20.

$$M = \tanh([W_h H; W_p P]) \tag{18}$$

$$\alpha = softmax(w_\alpha^T M) \tag{19}$$

$$v_\alpha = H\alpha^T \tag{20}$$

where $M \epsilon \mathbb{R}^{2d \times (n+2)}, W_h \epsilon \mathbb{R}^{d \times d}, W_p \epsilon \mathbb{R}^{d \times d}$, and $w_\alpha \epsilon \mathbb{R}^{2d}$ are projection parameters.

3.2. Module 2: Entity-Oriented Knowledge Dependency Convolutional Graph(EKDCG)

This section is further divided into subsections which are described in detail.

3.2.1. Knowledge layer

A knowledge graph consisting of named entities extracted from the phrases was built using YAGO (Rebele et al., 2016; Agichtein and Gravano, 2000; Bunescu and Pasca, 2006), which is a linked database created by Max Planck Institute researchers in Germany (Cambria et al., 2014). It compiles information from three primary sources—, GeoNames, WordNet, and Wikipedia,—in order to provide its results. YAGO's entity categorization system is robust as it combines vocabulary definitions from WordNet with Wikipedia's categorization scheme. In addition to this, YAGO provides attribute descriptions of geographical and temporal aspects for many knowledge entries, making it a comprehensive tool. To extract entity-oriented knowledge in sentences and mine the likely sentiment polarity of sentiment items, we utilized YAGO. A person may have positive attitude polarity toward the iPhone since it is the brand she prefers more when comparing three different brands of smartphones (such as Apple, Samsung, and Huawei). Another person who favors Huawei mobile phones, however, has a bad or ambivalent opinion of iPhones. To sum up, we extract the nouns and verbs from a sentence including a remark, and then we fuse the relevant knowledge about those nouns and verbs.

3.2.2. Entity-oriented knowledge dependency graph

Algorithm 2. Entity-Oriented Knowledge Dependency Graph

Input: *dependency tree* $T = (V, E_{edge})$, *where*
$V = v_1, \ldots, v_{|v|}, E_{edge} = (r_{ij}, v_i, v_j)$;
Output: Entity-Oriented Knowledge Dependency Graph
(KDG): $T_{KDG} = \left(V_{KDG}, E_{KDG}^{edge}\right)$
1: Entity list $E_{entity} = e_{entity}^1, \ldots, e_{entity}^K$
2: **for** entity $e_{entity}^i \epsilon E_{entity}$ **do**
$e_{KG}^i = K_{Query(t,\ K)}$; $T = K\_inject(t, e_{KG}^i)$;
3: **end for**

The Algorithm 2 explains how to build an Entity-Oriented knowledge Dependency Graph (KDG). Algorithm 2 takes YAGO K, dependency syntax tree T, and entities E extracted from sentences parsed by Biaffine and CoreNLP parsers as its inputs. The dependency graph is denoted by *T*.

$T = (V, E_{edge})$, where $V = \{v_1, \ldots\ldots v_{|V|}\}, E_{edge} = (r_{ji}, v_i, v_j)$. Here, we make use of the two procedures (i.e.,$K_Query(t, K)$ and $K_Inject\left(t, e^i_{edge}eiedge\right)$) of K-BERT (Jain et al., 2021) to inject knowledge about entities into the syntactic tree. Where EKG is a collection of triples providing knowledge information and can be expressed as follows, $K_Query(t_iti, K)$ selects all the entity names involved in the *ith* sentence tree *ti* to query their associated triples from *K* in Eq. 21.

$$E_{KG} = [(r_{i0}, w_i, w_{i0}), \ldots, (r_{ik}, w_i, w_{ik})] \tag{21}$$

To create the Entity-Oriented Knowledge Dependency Graph *t*, the *K* Inject(ti, EKG) operation inserts EKG into the sentence tree *t* by linking the triples in EKG to their appropriate nodes in the tree.

3.2.3. Context information representation

Sequence information is not contained in single words. Typically, we use the surrounding text to figure out what a term means. The importance of accurately portraying words in their proper contexts (Wu et al., 2020) cannot be overstated. In this study, a bidirectional LSTM (Bi-LSTM) model with a global context (Schuster and Paliwal, 1997) was employed to produce word embeddings and global context vectors that are enriched with contextual information. Building on previous research on ABSA (Ben Veyseh et al., 2020), the significance of syntactic information, particularly phrase structure, was also identified in collecting information about word collocation norms. Consequently, we provide the syntax path of each word to properly depict them. Supposing the length of the input sentence is s, we may write it as $w = w_i, \ldots, w_t, \ldots, w_{|s|}$, where w_t is the $t-th$ word. The word vectors $w_t \in R^d$ are initialized using BERT (Devlin et al., 2018), where *d* is the total number of word vectors as Eq. 22.

$$h_t = w_t + h^f_t + h^b_t + p_t \tag{22}$$

where h^f_t and h^b_t signify that the Bi-LSTM retains both historical and expected context for the string $w_{t t=1\ldots|s|}$, respectively. h_t are inputs for the ARGCN module; both global context and syntactic information are contained in h_t, directing information transfer in higher layers.

3.2.4. Attention-Based Relational Graph Convolutional Network (ARGCN)

In order to enclose the meticulously made graph of syntactic dependencies, we build on R-GCNs (Schlichtkrull et al., 2018) and add a distance-aware attention mechanism. This research proposes a relational graph convolutional network that may focus on a specific object of interest. Our model's major goal is to take into account the interplay between aspect words and entities in a unified manner, taking into account both semantic and contextual relevance. To keep their secret states up-to-date, R-GCNs (Schlichtkrull et al., 2018) aggregated the representations of their neighbors at each node based on the type of edges between them.

$$h'_i = \sigma\left(\sum_{r\epsilon\mathscr{R}}\sum_{j\epsilon\mathscr{N}^r_i} X_{ij,r} + W_1 h_i\right) \tag{23}$$

$$X_{ij,r} = \frac{1}{c_{i,r}} W_r h_j \tag{24}$$

where $\mathscr{R}$ is the collection of relations, h_i is the input representation of node v_i, h'_i is the output representation of node $v_i, \mathscr{N}^r_i ri$ is the set of neighbors of *vi* under relation $r\epsilon\mathscr{R}, W_r$ and W_1 are trainable parameters, and $c_{i,r}$ is a normalization constant that is problem-specific and is usually assigned as the number of neighbors of v_i under relation *r*. There is also a per-element activation function σ.

Each relation *r* in Eq. 24 is represented by a unique relational matrix W_r. We use a procedure called basis decomposition to cut down on the number of parameters (Schlichtkrull et al., 2018). Specifically, we decided on a single base:

$$W_r = b_r W_0 \tag{25}$$

where b_r is a function of *r* as a coefficient. The number of parameters is substantially decreased because all W_r use W_0 as their common base. However, b_r represents the level of impact with regard to relational categories. To increase RGCN's effectiveness, we add a distance-aware attention mechanism in ARGCN.

$$x_{ij,r} = \alpha_{ij,r} W_0 h_j \tag{26}$$

$$\alpha_{ij,r} = \sigma\left(c^T\left[b_r, \beta_{ij}\right]\right) \tag{27}$$

where *ij* is an attention coefficient for the pair w_i, w_j and *c* is a trainable vector that modifies both the relation and the attention coefficient. As an example of an activation function, we will employ ReLU in the ARGCN layers. We assume that node features and node position in the phrase jointly determine the attention coefficients between any two nodes. We start by multiplying the same projection matrix, W1, by the features of the nodes we're interested in, *hi* and *hj*, to get our query and key. Then, following the method of Dai et al. (2022), we obtain the sinusoid encoding matrix *p*, which encodes positions relative to one another. Then we pay attention to the query, the key, and the relative positional encoding using a shared attention mechanism:

$$o_{ij} = \sigma\left(a^T\left[W_1 h_j, W_1 h_i, p\right]\right) \tag{28}$$

where a is a scalar-to-vector mapping that can be trained from the concatenated representation. Finally, we use the Softmax function to standardize o_{ij} relative to all of w_i/s neighbors:

$$\beta_{ij} = \frac{\exp(o_{ij})}{\sum_{k\epsilon\mathscr{N}_i}\exp(o_{ik})} \tag{29}$$

where *ij* represents the weight given to $w_i by\ w_j$ in terms of the node representations and their relative position.

Further, including multi-head attention in our system helps to steady the learning process and boosts performance. Specifically, the modification of Eq. 30 is carried out using K-independent attention methods.

$$x^k_{ij,r} = \alpha^k_{ij,r} W^k_0 h_j \tag{30}$$

where d_j is the input dimension, d_k is the dimension of each head, and $W^k_0 \epsilon \mathbb{R}^{d_j \times d_k}$. In this case, the output of the multi-head attention mechanism by Eq. 31:

$$x_{ij,r} = W_d\left[x^1_{ij,r}, x^2_{ij,r}, \ldots, x^K_{ij,r}\right] \tag{31}$$

where $W_d \epsilon \mathbb{R}^{Kd_k \times d_{j+1}}$ preliminary experiments show that setting $d_k = d_{j+1}$ improves performance slightly compared to the method used by Vaswani et al. (2017), who used d_{j+1}/K as a dimension of each head. Syntactic dependency tree analysis reveals that phrases denoting aspects and opinions frequently have direct or indirect connections to one another in the graph. Using L-layers of ARGCN, we are able to capture these direct or indirect connections because, as we add more and more ARGCNs, more and more information is shared with our $L_{th}order$ neighbors. On top of that, as the network layers increase in depth, ARGCN becomes increasingly smooth. To address this issue, we embed a residual link into every layer of the ARGCN network:

$$h_i^{l+1} = h_i^l + h_i^{\prime l} \tag{32}$$

where h_i^l is the input to vi in the lth ARGCN layer and $h_i^{\prime l}$ is the output. Because of this, the input of the ARGCN's (l + 1) th layer is h_i^{l+1}. Boosting Contextual information a Bi-LSTM is incorporated into the input words to obtain their contextual information, and the resulting output hidden state hi is adopted as the initial representation h_i^0 of leaf node i. Next, we use the root's intermediate hidden state, represented by h_a^0, to encode the aspect word in a second BiLSTM. During Training Cross Entropy loss and l2-Regularization are used.

3.3. Output and learning

The output from both modules APA and EKDCG is connected through the dense layer and a fully connected softmax layer is used to map the probabilities of different sentiment polarities.

4. Experiment and analysis

The experiment and the details related to the experimentation process are presented in this section.

4.1. Dataset

We used five publicly accessible NLP datasets containing the English language to evaluate the proposed APEKCG model. MAMS, Laptop, Restaurant, AWARE, and SemEval-15&16 have been extensively utilized in prior studies (Wang et al., 2020; Chen et al., 2019a; Alturaief et al., 2021; Pontiki et al., 2016; Pontiki et al., 2015). Each line in the MAMS dataset has two aspects with opposite sentiment polarities (Ben Veyseh et al., 2020; Chen et al., 2022), making it a popular and difficult dataset for ABSA tasks. Aspect terms and their polarity (Wang et al., 2020; Pablos et al., 2015) have been tagged in more than 3 K English sentences in the Laptop dataset, which were annotated by skilled human annotators. Reviewers evaluate restaurants on various criteria such as meal quality, service, price, ambiance, and more, by employing coarse aspect categories of restaurants and annotating overall sentence polarity (Pablos et al., 2015; Wan et al., 2020). AWARE is an all-encompassing dataset that includes 11323 statements that contain the three areas combined. Each sentence that is included in the datasets has at least one Aspect Category and one Aspect Sentiment marked upon it (Alturaief et al., 2021). SemEval-2015 (Pontiki et al., 2016) and SemEval-2016 (Pontiki et al., 2015) datasets are the review data on the restaurant field. There is a lot of overlap between the SemEval-16 and SemEval-15 training data because they are both extensions of the SemEval-15 dataset, therefore we combined their training and testing data. Conflict information is omitted from the original data sets. A line like "not a large place, but it's cute and comfortable" would be categorized as having a "conflict" sentiment because of the "ambiance" aspect category. Only information marked as good, negative, or neutral is retained. Since there is insufficient "neutral" data in the SemEval-15&16 training set, models suffer greatly since the "neutral" category cannot be differentiated during training. To remedy this, we extend the training set with four additional copies of the original "neutral" data.

In each dataset, half of the documents from each author are used to create the training set, while the remaining half is used to create the testing set. The utilization of a 50–50 split in data allocation for training and testing purposes offers a rational equilibrium between the biases and variances encountered during model evaluation. This approach effectively addresses the challenges of overfitting and underfitting by finding an optimal compromise (Singh et al., 2021). Moreover, the 50–50 split attains a favorable trade-off between the computational efficiency of model execution and its overall performance (Trivedi et al., 2022). By dedicating a significant portion of the data for training, valuable patterns can be captured while still reserving a substantial subset for testing, thereby enabling an effective assessment of the model's proficiency with unseen instances (Krishna et al., 2021). Consequently, this partitioning is of utmost importance in comprehending the model's capacity to accurately handle novel, unobserved data samples. Table 6 provides other statistics on datasets.

These databases cover a wide range of topics, including people, places, food, services, the natural world, entertainment, consumer electronics, and more. Due to their expansive nature, these datasets cannot be reduced to the study of a single or even a small number of disciplines. In every experiment, the dataset is preprocessed, and all capital letters are changed to lowercase. Since the datasets utilized in the experiments lacked a validation set, we selected 10% of the training set's data samples randomly as the validation set to adjust the aforementioned hyperparameters. To ensure the impartiality of the comparison experiments, we also utilized this methodology. Furthermore, YAGO's knowledge base is heavily reliant on encyclopedic resources like Wikipedia, WordNet, and GeoNames. This research calls YAGO's sentiment analysis data "Entity-Oriented knowledge" to emphasize sentiment polarity.

4.2. Experiment settings

Each dataset utilized in this study undergoes a process of data cleansing, involving the removal of redundant, superfluous, or irrelevant information. In order to prepare textual data for analysis, several functions offered by the NLTK python library are employed, including Stop Word Removal, Stemming and Lemmatization, Normalization, and Tokenization. Stop-word removal eliminates insignificant words and symbols while stemming and lemmatization break down sentences into their constituent parts. Normalization ensures that sentences adhere to industry standards, and tokenization segments longer strings into smaller, more manageable units. Text normalization plays a critical role due to the prevalence of noise in online content and social media data, often taking the form of abbreviations, misspellings, and out-of-vocabulary words. To obtain a vector representation of text tokens, a pre-trained BERT word embedding is utilized. By undergoing pre-training on extensive data, BERT acquires a comprehension of natural language, which is subsequently fine-tuned for aspect-based sentiment analysis. BERT generates word embeddings that exhibit contextual awareness, wherein the representation of a word can vary depending on its surrounding context. This capability empowers BERT to effectively handle polysemous words (words with multiple meanings) and extract more nuanced information from textual data.

In this study, we use the following values for our experimental hyperparameters to make a fair comparison between our APEKCG and the reference models. The sentence tree is constructed with the Biaffine parser (Dozat and Manning, 2016) and Stanford CoreNLP parser (Manning et al., 2014) as dependency parsers. For model training, we employ Adam (Kingma and Ba, 2014) as the optimization function and initialize the word vector embedding with 300-dimensional BERT (Devlin et al., 2018) vectors. Overfitting can be avoided with the help of l2 - regularization, which is applied between the intervals of n as 0, 1×10^{-5}, 1×10^{-4}, 1×10^{-3},

Table 6
Dataset statistics.

Dataset	Positive Train	Positive Test	Negative Train	Negative Test	Neutral Train	Neutral Test	Aspect Categories
MAMS	1890	1890	1546	1546	2824	2824	8
Laptop	667	667	499	499	316	316	4
Resturant	1446	1446	501	501	416	416	4
AWARE	2656	2656	2645	2645	360	360	12
SemEval-15& 16	1214	1214	619	619	306	306	12

1×10^{-2}. The learning rate is 1×10^{-3} and it is halted based on the test set performance, Epoch 8, Batch size 16, Max sequence length 64, and the dropout rate is 0.2. We give the average Macro-F1 and accuracy across five distinct random seeds used in our trials. We've used the "Python 3.11" programming language on Windows 10 operating system for the evaluation of the proposed model. PyTorch was used on top of TensorFlow as the development framework for the code, and two GPUs are being utilized for the training of the models (NVIDIA GeForce GTX 2080Ti). The parameters in the baseline techniques are either used with their values from the original publication or many experiments are run to determine the optimal values. In order to get the best results using BERT as an embedding layer model, the settings are adjusted to match those suggested by the BERT developers.

4.3. Baseline models

We choose attention-based and syntax-based models as our benchmarks to ensure that our APEKCG is properly validated.

4.3.1. Attention-based models

The Target-Dependent LSTM (TD-LSTM) utilizes two TD-LSTMs to jointly learn target- and context-dependent word connections (Tang et al., 2015). Meanwhile, the Attention-based LSTM Network (ATAE) employs the attentional mechanism to reveal the polarity of the sentence's sentiment based on the content of the sentence and its relationship to the worrying component (Wang et al., 2016). Recurrent Attention on Memory (RAM) utilizes the multiple-attention mechanism to capture distant emotional characteristics (Chen et al., 2017). Interactive Attention Networks (IAN) are designed to learn attention in both contexts and targets to create autonomous representations for targets and contexts (Ma et al., 2017). The Multi-Grained Attention Network (MGAN) employs aspect alignment loss to depict aspect-level interactions between aspects that are in the same context (Fan et al., 2018). Finally, to monitor lexical representations in context and generate supplementary text, ABSA uses BERT (Hoang et al., 2019). Attention-based models for ABSA have limitations that include contextual overemphasis, lack of global context, sensitivity to input order, vocabulary limitations, and interpretability challenges (Nguyen and Shirai, 2015Veličković et al., 2017).

4.3.2. Syntax-based models

This paper discusses various attention strategies for the ABSA task that consider syntactic information. SynATT (Syntax-based LSTM) proposes an attention strategy that takes into account syntactic information (Nguyen and Le Nguyen, 2018). PhraseRNN, or Phrase Recursive Neural Network, improves upon the RNN model by taking into account the dependency and constituent trees of a sentence (Nguyen and Shirai, 2015). Graph neural networks like GAT (Graph Attention Networks) use masked self-attention to process graph-structured input (Chen et al., 2019a; Veličković et al., 2017). The Target-Dependent Graph Attention Network, TD-GAT, explicitly mines the dependency link between words (Huang et al., 2020). AS-GCN (Aspect-Specific Graph Convolutional Networks) leverages the dependency tree and syntactic information about words to improve the task (Zhang et al., 2019a). CDT uses Bi-LSTM to construct word representations and then uses GCN to enhance embeddings based on the dependency tree (Sun et al., 2019). SD-GCN (Dependencies on Emotion Sentiment Dependency Relationships in Multi-Aspect Sentences Captured by GCNs) captures dependency relationships in multi-aspect sentences through GCNs (Zhao et al., 2020). R-GAT (Relational Graph Attention Network) is an improved version of GAT that incrementally collects data. DualGCN combines a GNN with syntactic structures and semantic correlations (Li et al., 2021b). SenticGCN improves sentence dependency graphs by using sentiment knowledge from SenticNet (Liang et al., 2022). dotGCN provides a different structure than explicit dependence trees (Chen et al., 2022).

4.4. Results analysis

We apply the global classification accuracy and the macro F1-score as performance evaluation metrics to validate the performance efficacy of APEKCG when the training datasets are consistent. Table 7 compares the performance of APEKCG with other attention-based models, whereas Table 8 compares its performance with syntax-based models across all five datasets.

Through a comprehensive examination of Table 7 and Table 8, noteworthy insights can be gleaned from this research study. The investigation involved a comparative analysis of diverse models employed in ABSA, leading to the observation that models incorporating dependency trees, namely R-GAT, GAT, SD-GCN, ASGCN, LSTM + SynATT, and DT-GAT, outperform those relying solely on attention mechanisms. The findings underscore the significance of syntactic information in ABSA. However, attention-based models such as IAN, MGAN, RAM, and BERT exhibit greater effectiveness than RNN-based models like ATAE-LSTM and DTLSTM in capturing aspect-sentiment associations. Among the structured models, two prominent categories emerge as superior performers: tree-LSTM-based tree neural networks (e.g., PhraseRNN, LSTM + SynATT) and GNNs enhanced with dependency information (e.g., R-GAT, GAT, SD-GCN, ASGCN, DT-GAT). These outcomes highlight the superiority of GNNs in tackling the ABSA task.

Furthermore, we delve into the examination of two additional models, namely DualGCN and Sentic GCN, which incorporate a combination of syntactic and sentiment knowledge in their computational processes. This innovative approach leads to a notable improvement in the accuracy of sentiment prediction within these models. The empirical outcomes, as depicted in Table 8, substantiate that the fused knowledge model outperforms the structured-based modeling technique, thereby underscoring the significance and reliability of incorporating prior information in 8 sentiment analysis. In light of these findings, it becomes evident that the integration of both syntactic and sentiment information is of paramount importance in ensuring precise and reliable sentiment analysis outcomes.

Moreover, our proposed APEKCG model, incorporating fused entity-oriented knowledge, surpasses the R-GAT model in terms of performance across all evaluated metrics. Previous research, specifically, the study (Jain et al., 2021) has established the significance of entity-oriented information in determining the polarity of users' sentiments toward a particular product or service. Leveraging this valuable insight, the APEKCG model integrates such entity-oriented knowledge, resulting in further improved outcomes in sentiment analysis tasks.

Structured models that utilize syntactic trees, such as syntax and dependency trees, are widely used to model GNNs in both structured and fused knowledge models. These include SynATT, TD-GAT, SD-GCN, DualGCN, and Sentic GCN. In contrast, serialized models such as ATAE, DT-LSTM, RAM, IAN, and MGAN demonstrate inferior performance in capturing sentiment. This highlights the importance of structure-based models in sentiment analysis. The incorporation of syntactic and sentiment knowledge, along with entity-oriented knowledge, significantly enhances the accuracy of sentiment analysis models. Therefore, it is clear that the utilization of these methods can greatly improve the effectiveness of sentiment analysis techniques.

Our APEKCG model outperforms all other models. APEKCG is a technique that combines aspect position attention learning and entity-oriented knowledge dependency convolutional graph. Experimental results show that incorporating aspect attention learning, entity-oriented knowledge, dependency labels, and syntax path together can lead to improved performance in the ABSA task. Furthermore, the use of dependency data is effective in identifying sentiment pairs, regardless of their proximity or relationship to sentiment polarity. Nonetheless, this has been proven for a number of NLP tasks (Wu et al., 2021; Zhang et al., 2022c), using the syntactic approach, entity-oriented knowledge, and data from dependency labels to better recover latent semantic information influencing sentiment polarity. Also, using a pre-trained language model like BERT can improve the model's ability to learn latent information.

In addition, we have conducted a comparative analysis between our proposed APEKCG model and the leading-edge models in the field. We have utilized the findings from the original research studies, and our proposed model has exhibited superior performance in terms of accuracy and F1 score when compared to the state-of-the-art methodologies, shown in Table 9.

Moreover, we have evaluated our proposed model based on the weighted F1 score, as it is a valuable evaluation metric that brings several advantages to model assessment. Firstly, it addresses the challenge of class imbalance by considering the distribution of samples across classes, shown in Table 10. This ensures that the evaluation is not biased towards the majority class and gives appropriate weightage to each class based on their representation in the dataset (Jangid et al., 2018). Secondly, the weighted F1 score provides a holistic measure of model performance by combining precision and recall for each class. It takes into account both the positive and negative predictive values, giving a comprehensive assessment of the model's ability to correctly classify instances from all classes. Additionally, the weighted F1 score reflects the practical importance of different classes. By assigning higher weights to classes with larger sample sizes, it highlights the performance of classes that may have greater significance in the specific application or problem domain. Additionally, the weighted F1 score allows for fair comparisons across models or variations of the same model. It provides a consistent evaluation metric that accounts for class distribution, ensuring that models are assessed on an equal footing (De Greve et al., 2021).

Table 7
Comparison with attention-based models.

Datasets	Models	Accuracy	Macro-F1
MAMS	BERT	82.82	81.90
	Proposed APEKCG	**89.13**	**87.56**
Laptop	ATAE	68.70	-
	DT-LSTM	71.22	65.75
	RAM	74.49	71.35
	IAN	72.10	-
	MGAN	75.39	72.47
	BERT	77.58	72.38
	Proposed APEKCG	**84.32**	**80.59**
Restaurant	ATAE	77.20	-
	DT-LSTM	79.10	69.00
	RAM	80.23	70.80
	IAN	78.60	-
	MGAN	81.25	71.94
	BERT	83.62	78.28
	Proposed APEKCG	**89.02**	**83.95**
AWARE	DT-LSTM	69.51	67.98
	RAM	69.36	67.30
	MGAN	72.54	70.81
	BERT	75.28	74.11
	Proposed APEKCG	**79.64**	**78.55**
SemEval-15& 16	ATAE	77.15	62.70
	DT-LSTM	80.79	70.43
	RAM	76.17	64.33
	IAN	74.28	60.38
	MGAN	81.84	72.10
	BERT	89.19	82.54
	Proposed APEKCG	**90.22**	**85.66**

Table 8
Comparison with syntax-based models.

Datasets	Models	Accuracy	Macro-F1
MAMS	CDT	80.70	79.79
	R-GAT	81.75	80.87
	dotGCN	85.95	84.44
	Proposed APEKCG	**89.13**	**87.56**
Laptop	SynATT	77.57	69.13
	GAT	73.04	68.11
	ASGCN	75.55	71.05
	TD-GAT	74.13	72.01
	CDT	77.19	72.99
	SD-GCN	81.35	78.34
	R-GAT	78.21	74.07
	DualGCN	80.63	77.36
	Sentic GCN	81.35	77.90
	dotGCN	81.03	78.10
	Proposed APEKCG	**84.32**	**80.59**
Restaurant	PhraseRNN	66.20	59.32
	SynATT	80.45	71.26
	GAT	78.21	67.17
	ASGCN	80.77	72.02
	TD-GAT	80.35	76.13
	CDT	82.30	74.02
	SD-GCN	83.57	76.47
	R-GAT	86.60	81.35
	DualGCN	86.77	81.62
	Sentic GCN	86.94	81.62
	dotGCN	86.15	80.37
	Proposed APEKCG	**89.02**	**83.95**
AWARE	GAT	71.67	70.13
	ASGCN	72.15	70.40
	TD-GAT	72.68	71.15
	CDT	74.66	73.66
	R-GAT	76.15	74.88
	DualGCN	76.04	74.91
	Sentic GCN	76.22	74.90
	dotGCN	78.11	77.00
	Proposed APEKCG	**79.64**	**78.55**
SemEval-15& 16	AGAT	74.28	60.38
	ASGCN	81.84	72.10
	TD-GAT	89.19	82.54
	CDT	88.15	80.38
	R-GAT	88.41	80.95
	DualGCN	90.62	79.19
	Sentic GCN	89.45	81.46
	dotGCN	89.55	82.71
	Proposed APEKCG	**90.22**	**85.66**

We have used McNemar's non-parametric test to compare the results of several approaches to see if there was a statistically significant difference in performance (Dietterich, 1998). This test has been used in similar investigations and does not assume normally distributed data, making it ideal for our objectives (Chen et al., 2019b). Specifically, using McNemar's test, we need to keep track of how many samples are correctly categorized as A rather than B (denoted as n_{10} in Eq. 33) and and how many are correctly categorized as B rather than A (denoted as n_{01} in Eq. 33). We can then calculate the statistical significance:

$$x^2 = \frac{(|n_{01} - n_{10}| - 1)^2}{n_{01} + n_{10}} \tag{33}$$

This has a 2 distribution with one parameter. Only if the p-value of the computed statistic falls below a predefined threshold is there evidence of a statistically significant difference in performance. Table 11 and Table 12 display the statistical data; we chose a 5% level of significance. It is clear from the results that our suggested APEKCG model outperforms the baseline approaches on all five datasets. Table 11 and Table 12 present the p-value that emerges from McNemar's test results on all five datasets.

Table 11 and Table 12 clearly demonstrate that the proposed model APEKCG, when compared to each baseline model, exhibits a p-value below the threshold value of 0.05. As a result, we can reject the null hypothesis and conclude that the performance of the two models differs significantly. Notably, APEKCG, with its higher mean accuracy, has significantly outperformed the applied baselines.

4.5. Ablation studies

Additionally, we conducted ablation studies to further validate the impact of individual components within the APEKCG framework. The findings of these studies are presented in Table 13, where the abbreviation "w/o" represents "without." Notably, Table 13 provides empirical evidence illustrating the substantial decline in accuracy of the APEKCG model when crucial elements such as APA, EKG, BERT, Bi-LSTM, dependency labels, entity-oriented KG, syntax route, and position embedding module are removed. This observation strongly suggests that the utilization of all the information incorporated in this research can significantly enhance the accuracy of the APEKCG model in addressing the ABSA task, as represented in Fig. 2. Remarkably, the most drastic decrease in accuracy occurs with the removal of BERT, followed by dependency labels, syntactic route, Entity-oriented Knowledge Graph, Bi-LSTM, and finally the position embedding module.

Drawing upon previous research (Li et al., 2022c; Ma et al., 2018), it can be inferred that the Bi-LSTM model possesses the capability to effectively capture the semantic context of words. This observation further highlights the significant role of contextual semantic information in influencing the expression of emotions. In simpler terms, the Bi-LSTM model can be regarded as a powerful tool for analyzing the impact of contextual semantic information on emotional expression. Representing the explicit relational semantics of sentiment pairs more accurately, entity-oriented knowledge graphs offer a valuable advantage. Moreover, neglecting this aspect leads to a decrease in the accuracy rate, suggesting that domain-specific information enhances sentiment analysis. In contrast to implicitly modeling the proposed APEKCG model, incorporating dependency labels enables the explicit modeling of APEKCG and facilitates the integration of its outcomes with other data in a high-dimensional vector space. Lastly, the syntactic approach allows for more efficient extraction of collocation information between words, particularly when different words with varying degrees of polarity are employed to modify distinct sentiment elements.

4.6. Discussion

In our study, we developed a model called APEKCG, which comprised two distinct modules. Each module was constructed independently, and subsequently, their outputs were fused together to generate the final output of the model. To assess the impact of various factors, such as different parsers, GCN layers, suggested parameter settings, and other relevant variables, on the performance of our APEKCG model, we conducted a series of four comprehensive tests. These tests were designed to investigate and evaluate the influence of these factors on the overall effectiveness and functionality of the APEKCG model.

4.6.1. Impact of using various parsers

We tested our model with two popular dependency parsers (i.e., Biaffine Parser, and Stanford CoreNLP Parser (Chen and Manning, 2014)) to confirm the effect of dependent parsers on the ABSA job. Consistent with other research (Inui et al., 2019; Qi et al., 2020), Table 14 experimental results show that ABSA task performance varies between dependency parsers. Biaffine outperforms CoreNLP at discovering interdependencies between sentiment elements and polarity. Enhancing the efficiency of the dependency parser can result in a more precise ABSA task performance, especially when working with complex textual information like sentiment analysis, particularly in the case of challenging datasets. In other words, by improving the efficiency of the dependency parser, it is possible to enhance the accuracy and effectiveness of sentiment analysis techniques, particularly when dealing with difficult datasets that may contain complex and nuanced information. Table 14 shows the performance of several parser tools. APEKCG + Biaffine shows superior performance on all datasets.

4.6.2. Layers of GCN's Effect

In our study, we employed several models, namely BERT, SD-GCN, dotGCN, and APEKCG, to analyze the Restaurant dataset. The primary objective was to examine whether the number of GCN layers had an impact on accuracy. As depicted in Fig. 3, the most favorable outcomes were achieved by the three CNNs (SD-GCN, dotGCN, and APEKCG) that incorporated both dependency

Table 9
Evaluations based on state-of-the-art methods.

Datasets	Laptop		Restaurant		MAMS	
Method	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
MWGCN (Yu and Zhang, 2023)	79.78	76.68	86.36	80.54	-	-
MultiGCN (Ma et al., 2023)	78.8	74.97	83.82	77.1	83.61	82.73
RGAT (Wu et al., 2022b)	78.02	74	83.55	75.99	81.75	80.87
SSK-GCN + BERT (Zhao et al., 2023a)	83.11	79.63	88.96	83.44	-	-
SA-BERT (Mewada and Dewang, 2023)	83.21	78.77	87.24	81.19	-	-
SA-BERT-XGBoost (Mewada and Dewang, 2023)	85.01	78.9	87.86	81.64	-	-
CLF-TrLSTM + Bert (Zhang et al., 2023)	82.99	79.49	88.33	83.08	-	-
Proposed APEKCG	**84.32**	**80.59**	**89.02**	**83.95**	**89.13**	**87.56**

Table 10
Evaluations of the proposed APEKCG based on weighted f1 score.

Datasets	Class	Precision	Recall	F1 Score	Samples	Weight	Weighted F1
MAMS	Positive	0.8941	0.842	0.8673	1890	0.3	0.2602
	Negative	0.7850	0.7987	0.7918	1546	0.25	0.1979
	Neutral	0.9000	0.8750	0.8873	2824	0.45	0.3993
Total					6260	1	0.8574
Laptop	Positive	0.8348	0.8400	0.8374	667	0.45	0.3768
	Negative	0.8262	0.8025	0.8142	499	0.34	0.2768
	Neutral	0.8260	0.8947	0.8590	316	0.21	0.1804
Total					1482	1	0.8340
Restaurant	Positive	0.9350	0.8782	0.9057	1446	0.61	0.5525
	Negative	0.8320	0.7250	0.7748	501	0.21	0.1627
	Neutral	0.9010	0.7963	0.8454	416	0.18	0.1522
Total					2363	1	0.8674
AWARE	Positive	0.8148	0.7482	0.7801	2656	0.47	0.3666
	Negative	0.8100	0.7147	0.7594	2645	0.47	0.3569
	Neutral	0.8630	0.7412	0.7975	360	0.06	0.0478
Total					5661	1	0.7714
SemEval-15&16	Positive	0.9486	0.8145	0.8765	1214	0.57	0.4996
	Negative	0.8536	0.7892	0.8201	619	0.29	0.2378
	Neutral	0.9450	0.8420	0.8905	306	0.14	0.1247
Total					2139	1	0.8621

Table 11
Comparison on the basis of McNemar's statistics on MAMS, Laptop, and Restaurant datasets.

Dataset	MAMS	MAMS	Laptop	Laptop	Restaurant	Restaurant
Method	x^2	**p**	x^2	**p**	x^2	**p**
ATAE	-	-	59.172*	0	882.049*	0
DT-LSTM	-	-	60.500*	0	761.274*	0
RAM	-	-	77.778*	0	333.638*	0
IAN	-	-	79.587*	0	223.017*	0
MGAN	-	-	52.112*	0	323.218*	0
BERT	4.696*	0.03	5.470*	0	9.339*	0.002
SynATT	-	-	8.817*	0.019	292.638*	0
GAT	-	-	4.516*	0.034	277.095*	0
ASGCN	-	-	0.329	0.566	-	-
TD-GAT	-	-	0.011	0.915	3.556	0.059
CDT	0.404	0.525	57.309*	0	963.628*	0
SD-GCN	-	-	55.249*	0	835.706*	0
R-GAT	0.012	0.914	72.901*	0	350.216	0
DualGCN	-	-	71.405*	0	255.314*	0
Sentic GCN	-	-	49.091*	0	368.057*	0
dotGCN	0.085	0.771	4.938*	0.026	22.830*	0

*This implies that the outcome bears statistical significance at a significance level of 5%.

Table 12
Comparison on the basis of McNemar's statistics on AWARE and SemEval-15 & 16 datasets.

Dataset	AWARE	AWARE	SemEval-15&16	SemEval-15&16
Method	x^2	**p**	x^2	**p**
ATAE	-	-	106.313*	0
DT-LSTM	364.618*	0	95.508*	0
RAM	354.211*	0	54.179*	0
IAN	-	-	136.172*	0
MGAN	18.817*	0.003	45.039*	0
BERT	14.516*	0.034	0.736	0.391
SynATT	-	-	0.761	0.097
GAT	18.618*	0	0.456	0.5
ASGCN	18.618*	0.004	2.913	0.088
TD-GAT	8.028*	0.005	1.432	0.231
CDT	0.059	0.838	118.534*	0
SD-GCN	-	-	71.969*	0
R-GAT	0.48	0.488	129.063*	0
DualGCN	18.618*	0	160.507*	0
Sentic GCN	8.028*	0.005	64.574*	0
dotGCN	11.653*	0.001	0.48	0.488

*This implies that the outcome bears statistical significance at a significance level of 5%.

and contextual information. This suggests that GNNs exhibit superior information capture capabilities compared to sequential models like BERT.

Furthermore, our research revealed that, except for two instances, the accuracy of GNNs did not demonstrate improvement with an increase or decrease in the number of layers. These

Table 13
Ablation Study of the proposed APEKCG model.

	Model	MAMS	Laptop	Restaurant	AWARE	SemEval-15&16
1	Proposed APEKCG	**89.13**	**84.32**	**89.02**	**79.64**	**90.22**
2	w/o APA	85.34	80.66	86.32	78.23	86.45
3	w/o EKG	86.74	81.32	87.01	77.64	88.22
4	w/o BERT	85.33	80.11	85.29	76.43	87.37
5	w/o LSTM	82.19	81.19	86.38	77.22	88.37
6	w/o Dependency Label	80.32	79.95	86.10	76.86	87.24
7	w/o KG	81.76	80.96	87.17	76.48	87.29
8	w/o Syntax Path	81.45	80.21	86.96	76.30	87.88
9	w/o position embedding module	81.23	80.13	86.02	76.03	87.12

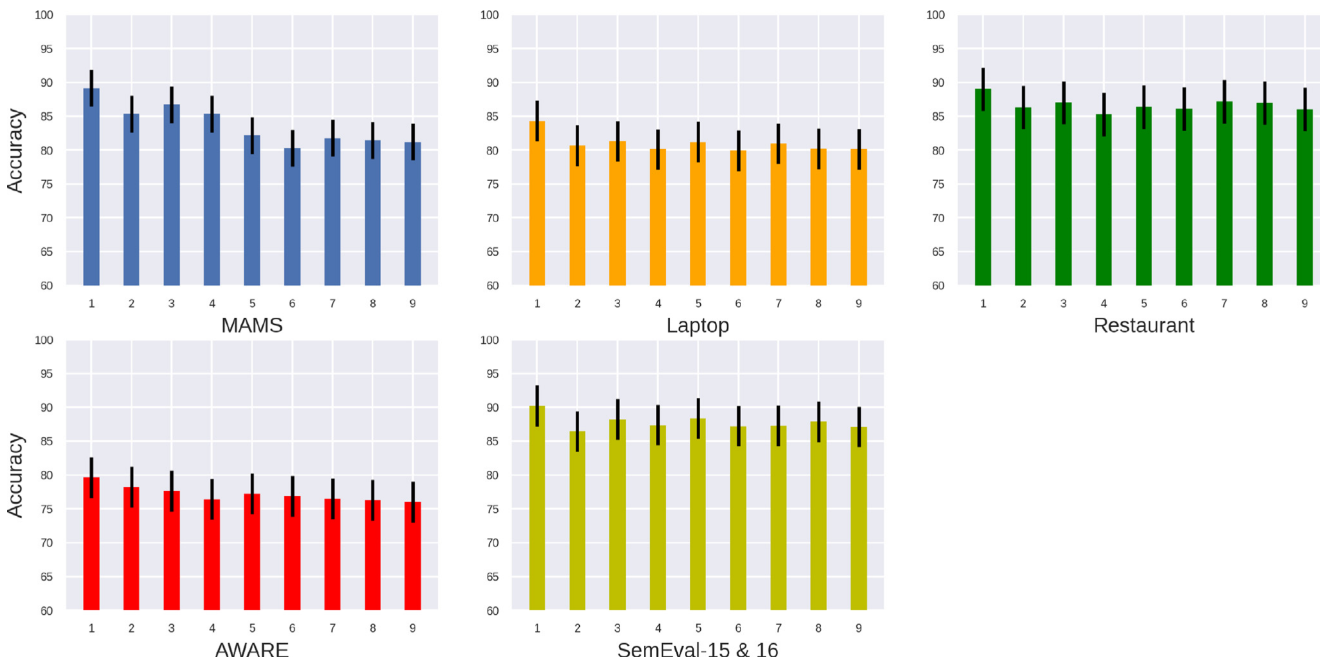

Fig. 2. Representation of ablation Study of the proposed APEKCG model.

findings align with previous studies (Nadeem et al., 2022), indicating that augmenting the number of GCN layers enhances accuracy in the ABSA task. As a result, future investigations will continue to delve into the influence of the number of GCN layers on accuracy. Additionally, we plan to explore other factors that may influence model performance, such as the selection of specific layers and the utilization of different types of data. These endeavors will contribute to a deeper understanding of the factors affecting model performance and guide the development of more robust and accurate sentiment analysis models.

4.6.3. Influence of the suggested parameter

In module 1, we have observed that We advocate using a wide range in tests for the location embedding rate, which fluctuates with text length, so we recommend using a wide range in trials and big step size to choose candidate values and validate the optimal value. You can see how modifying the value of affected our models' performance in Fig. 4. We use classification accuracy and the macro F1-score to gauge the model's effectiveness. We train the model using the determined value of, and finally, we select the best possible outcome for further examination.

4.6.4. Effects of several aspects

The ABSA task involves different datasets with numerous aspect terms in each sentence. It is important to investigate whether this phenomenon has an impact on the effectiveness of our APEKCG model. Based on sentence aspect terms, we evaluated the training accuracy difference between the Restaurant and MAMS datasets. We excluded samples with more than seven aspects because the sample size of such objects is too small for meaningful comparison, as previously noted (Li et al., 2019). In Fig. 5, we observe that the accuracy of our APEKCG model varies when there are more than three sentiment components in a text. This shows that the current model may not successfully preserve the dependencies of multiple sentiment components in a phrase and that new models will be needed in the future to address this difficulty. Understanding the impact of the number of aspect terms in a sentence is critical to improving the performance of ABSA models. This analysis can help

Table 14
Results the proposed APEKCG model on Stanford CoreNLP and Biaffine Parser.

Parser	MAMS	Laptop	Restaurant	AWARE	SemEval-15&16
CoreNLP	88.33	81.89	86.33	76.89	88.62
Biaffine	**89.13**	**84.32**	**89.02**	**79.64**	**90.22**

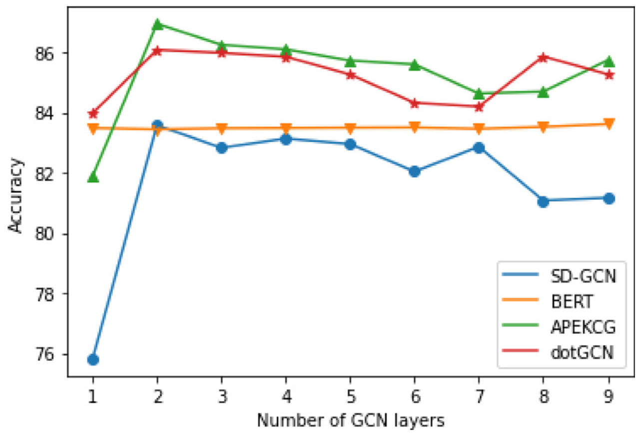

Fig. 3. Impact of GCN layers on accuracy.

researchers identify potential limitations in their models and develop more accurate methods for capturing sentiment components in a sentence. By developing more sophisticated models that can effectively capture the dependencies between different sentiment components, we can enhance the accuracy of sentiment analysis and provide more useful insights into the sentiment expressed in texts.

4.7. Case study

A related case study has been presented in this section.

4.7.1. Qualitative evaluation

In this section, we exhibit the prediction results of the proposed models by selecting some qualitative examples at random from the test data of SemEval-15 & 16 datasets. Table 15 presents a number of cases that were analyzed using various models, such as dotGCN, SD-GCN, SenticGCN, and ATAE. In these cases, the letters N_y, O_y, and P_y were used to indicate the presence of negative, neutral, and positive emotions, respectively, and the letters N_n, O_n, and P_n were used to indicate the absence of negative, neutral, and positive emotions, respectively. In Table 15, We have enclosed some words in square brackets to highlight their distinctive emotional connotations.

An illustrative example can be observed in the first instance, where the term “definitely” is utilized. This word carries a virtual hypothetical tone that contradicts the captured affective polarity, thereby introducing complexity in sentiment analysis. These findings underscore the significance of not only examining the proximity of words but also taking into account the broader semantic context when conducting sentiment analysis. The inclusion of words with nuanced meanings, such as “definitely,” highlights the necessity of a comprehensive approach that considers the overall tone and contextual information in order to accurately interpret and analyze sentiments. The second sentence example presented highlights the presence of the term “good” in close proximity, thereby eliciting attentional mechanisms in models such as ATAE. Although dependency relationships can effectively capture pairs of sentiment items and their corresponding sentiment polarity, it is important to acknowledge that they are still influenced by the semantic information encompassing the entire sentence. In other words, the interpretation of sentiment is not solely based on the individual relationships between words but also takes into consideration the broader context and meaning conveyed by the sentence as a whole.

To improve the capture of sentiment pairings, SenticGCN integrates sentiment knowledge based on dependency tree modeling. In contrast to dotGCN, which only alters the distance between words, these models perform better when there are many emotion pairs. When there is only one possible emotional reaction, as in the fourth case, the statement is not optimized. On the other hand, our APEKCG model combines BERT, syntax route, and Bi-LSTM to effectively capture the possible rules for how words can be put together, especially when it comes to sentiment terms, as well as the whole meaning of the sentence.

Initially, it is important to note that there are instances where sentences consist of a single aspect category. Such sentences often feature strong emotional expressions, as demonstrated by the term “uncomfortable” in Example 3. In these cases, all the models in comparison exhibit a consistent ability to accurately determine the sentiment direction conveyed within these sentences. However, when confronted with scenarios such as Example 5, where the polarity of certain aspects is more nuanced, the performance of the ATAE model tends to be subpar in comparison to our purposed APEKCG model. This observation implies that while the ATAE model may struggle in cases where the polarity of specific aspects is more complex, the proposed APEKCG model displays greater robustness and effectiveness. The APEKCG model’s ability to leverage the comprehensive knowledge graph representation of aspect-property-entity relationships allows for a more nuanced understanding of sentiment, particularly when encountering sentences with intricate polarity dynamics. By capturing and incorporating this extensive semantic information, the APEKCG model demonstrates superior performance and accuracy in sentiment analysis tasks compared to the ATAE model.

4.7.2. Attention visualization

To further confirm the efficacy of our APEKCG model’s individual parts (like BERT, syntax path, dependency labels, and entity-oriented knowledge, aspect location attention). In this example, we pull the text “the cake is delicious and the price is affordable” at random from Restaurant and display it in a new window using the attention method. Fusion of aspect position module, BERT, entity-oriented knowledge, and dependency labels was used to alter the original text. We see that the sentence’s focus might be split between two different aspect categories. Attention is like a gradient, with darker shades indicating a more focused study. Hence, the darker the hue, the more weight the word in that section carries. The successful identification of emotional information pertaining to specific aspect categories by APEKCG indicates that it is in line with human judgment on semantic emotion in natural language. In other words, the technique is able to accurately identify emotional information in relation to specific aspects, in a way that is comparable to how humans perceive and interpret semantic emotions in language. This highlights the potential value of APEKCG in accurately identifying and analyzing emotional information within natural language, particularly in the context of sentiment analysis. As per Example 2, the line “The restaurant isn’t very big but we got the table right away” does not contain the given aspect-categories “service” or “ambiance” in direct terms. This is a significant challenge since the machine cannot grasp the gist of the statement in the same way that a human can. So, we can see that our model is successful, at least to some extent, in understanding the gist of the text’s meaning. As can be observed in Fig. 6 and Fig. 7, APEKCG also pays little attention to the prepositions and punctuation marks in the text. That follows the accepted reasoning for determining the positive or negative nature of an expression of emotion: we pay no attention to these everyday terms. APEKCG pays close attention to and places a substantial emphasis on, words that are both relevant to aspect categories and typical of the sentiment being judged. As a result, we draw the conclusion that our APEKCG attention mechanism successfully models the text’s overall semantics.

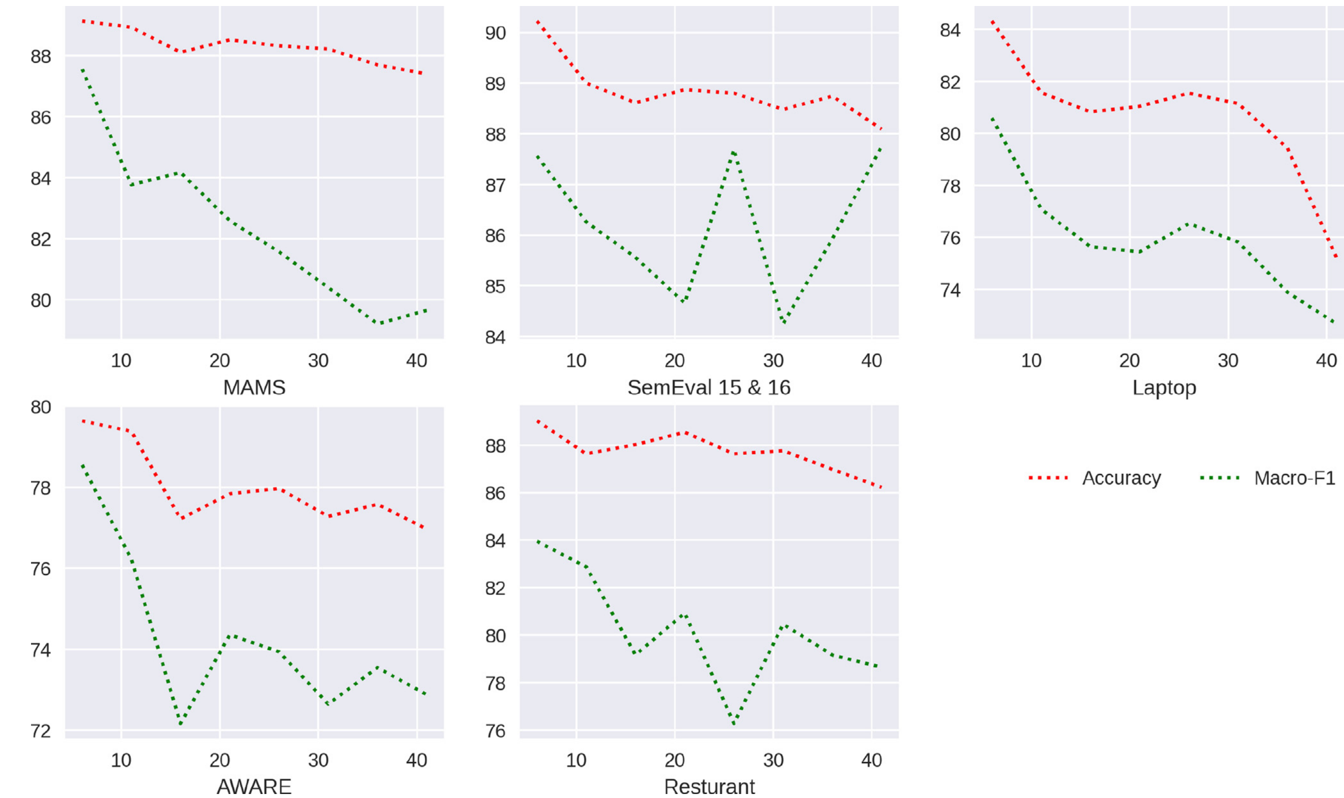

Fig. 4. Impact of different values parameter.

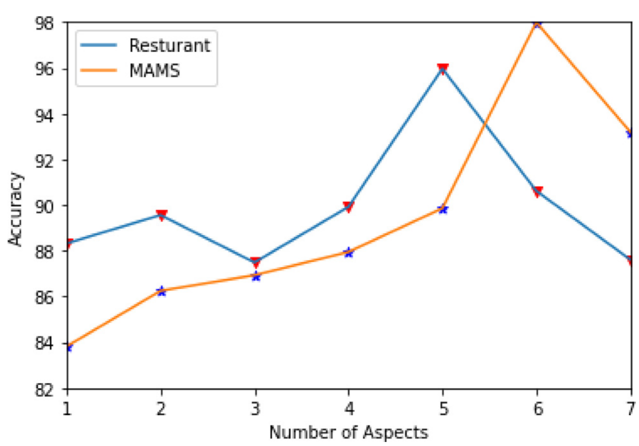

Fig. 5. Impact of number of aspects on accuracy.

5. Theoretical and practical implications

In our research, we presented a novel framework for Aspect-Based Sentiment Analysis that centers on the notion of information relevance. The proposed framework is meticulously developed through a comprehensive review of relevant literature in the field. Our proposed model is specifically crafted to effectively incorporate aspect categories alongside contextual information. To enhance aspect-specific sentiment analysis, we employed a boosted attention network coupled with aspect-position embedding. Furthermore, we integrate entity-oriented knowledge into our model's dependency tree structure by leveraging an Entity-oriented Knowledge Dependency Convolutional Graph. This incorporation facilitated the modeling of both implicit and explicit sentiment, as well as the analysis of single statements encompassing multiple emotions.

Diverging from prior investigations that predominantly examined general consumer sentiment, our study adopted a distinct approach by directing attention toward the identification and analysis of sentiment pertaining to particular aspects that hold significance for consumers. We acknowledged the inherent variability in the importance attributed to various facets of the customer experience, recognizing that certain aspects warrant greater attention than others. Through the integration of ABSA into our predictive modeling framework, we were able to offer businesses a comprehensive and practical assessment of sentiment for each individual aspect. This enhanced level of granularity empowered businesses to allocate their resources in a more targeted and efficient manner, enabling them to make informed decisions based on the specific sentiments associated with each aspect.

Table 15
Comparisons of the predictions based on examples.

Text	dotGCN	SD-GCN	SenticGCN	ATAE	APEKCG
Definitely try [calamari], any [pasta], or even the [sliced steak]	P_y, O_y, N_y	P_y, N_n, N_y	O_y, O_y, N_y	P_y, N_n, O_y	$P_y, O_y P_y$
The [food] is very good but the [location] is too far	P_y, P_n	P_y, N_y	P_y, N_y	P_y, N_y	P_y, N_y
The folding chair I was searing at was very [uncomfortable].	N_y	N_y	N_y	N_y	N_y
The staff should be a bit more [friendly].	P_n	N_y	p_n	P_n	N_y
I wish I had a [webcam] though, it would be [perfect].	P_n, P_y	P_n, P_y	O_n, O_y	N_y, N_n	N_y, P_y

Fig. 6. Case 1- the implicit aspect-categories.

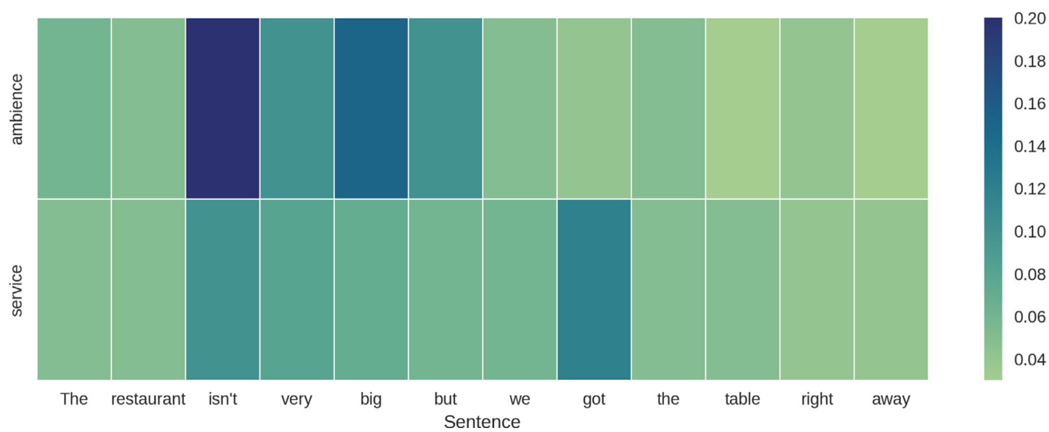

Fig. 7. Case 2- the explicit aspect-categories.

The pragmatic ramifications of our research underscore the significance of businesses engaging in active monitoring of online feedback as a means to bolster their operational effectiveness and long-term viability. Through the utilization of our proposed model, businesses gain the ability to discern and prioritize the pivotal factors that exert influence on their performance, thus enabling them to allocate resources in an optimized manner. By adopting this approach, businesses can enhance their decision-making processes, leading to favorable outcomes and advancements in the quality and delivery of their products and services.

6. Conclusions and future work

This research suggested a novel model APEKCG, which consisted of two modules APA and EKDCG. For the ABSA task, we suggest using an APA module to store information in a neural network's memory using an embedding of aspects and an attention mechanism based on aspects. New attention models (APAs) can be created by combining aspect-position embedding with the concept of attention, with the latter giving additional weight to the semantic relationship between words within the sequence. Our second module EKDCG uses reliance labels and syntactic paths to take into account domain knowledge (such as entity oriented) in addition to traditional measures of dependency. The experimental findings on five benchmark datasets demonstrate the superior accuracy of our proposed APEKCG model for the ABSA task (i.e., MAMS, Laptop, Restaurant, AWARE, and SemEval 15 & 16). In addition, we show that Entity-Oriented knowledge, syntax route, and the dependency labels of the EKDCG model can improve the model's accuracy by conducting Ablation Studies and a Case Study. Furthermore, the visual representations of attention weights demonstrate APEKCG's ability to sensibly focus on the unique information in the input text, which is crucial for determining the polarity of sentences' sentiments. Moving forward, we aim to incorporate neurosymbolic AI to enhance explainable sentiment analysis, as well as integrate additional types of knowledge, such as syntax, semantic, and inference knowledge, into the ABSA task. One key challenge we intend to address is the issue of neutrality/ambivalence, which can be difficult to capture accurately with traditional sentiment analysis methods. To achieve this, we plan to develop and test several syntactic models to explore the impact of syntactic parsing tools on model accuracy and resilience. This will allow us to better understand the role of syntactic information in sentiment analysis and potentially develop more effective models for capturing nuanced sentiment. By incorporating multiple sources of knowledge and exploring new modeling techniques, we hope to improve the accuracy and reliability of ABSA models. This will enable us to better understand the sentiment expressed in texts and provide more insightful and meaningful analyses to users. Ultimately, our goal is to develop more advanced and sophisticated ABSA models that can accurately capture and analyze the full spectrum of sentiment in texts.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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