**AI-driven key phrase extraction in teaching English writing skills**

*Duc Huu Pham, The School of Languages,*

*International University, Vietnam National University Ho Chi Minh City*

*Email: phduc@hcmiu.edu.vn*

**Abstract**

The integration of artificial intelligence (AI) into language education is revolutionizing the field of the teaching and learning of English by providing innovative tools for both teachers and learners. This paper examines the application of AI-powered key phrase extraction as a means to enhance the teaching and learning of writing skills among English language learners. Key phrase extraction, enabled by advanced natural language processing models such as keyBERT, which allows for the automatic identification of essential words and phrases that encapsulate the main ideas of a text. By leveraging these technologies, teachers can help students develop writing skills. In writing instructions, AI-driven key phrase extraction supports learners in summarizing and organizing their ideas, maintaining thematic coherence, and self-assessing the clarity of their arguments. The paper discusses both the theoretical foundations and practical classroom strategies for implementing key phrase extraction. Ethical considerations, such as data privacy and algorithmic bias, are also addressed. AI-driven key phrase extraction offers a promising approach to making language learning more effective, personalized, and engaging in the digital age.

**Keywords**: artificial intelligence (AI), keyBERT model, key phrase extraction, natural language processing (NLP), TESOL (teaching English to speakers of other languages), writing skills

**1. Introduction**

In recent years, key phrase extraction has become an important resource in language teaching, especially when digital content has placed semantic interpretation in an important position in approaches of language teaching. Key phrases can help students to get main ideas of a text and assist English students in interpreting the meaning and significance of language. English teachers can help students to identify and use key phrases to develop effective writing. Extracting key phrases from texts used to be time-consuming and manual. However, up to now, recent developments in natural language processing (NLP) and artificial intelligence (AI) have made this exercise more effective. AI-based key phrase extraction can now make it possible for us to have the automatic detection of the most salient words or phrases in a text. By incorporating these AI-based methods into language teaching, teachers can assist students in managing the intricacies of English texts, and at the same time, building the critical literacy proficiency that is demanded for academic achievement.

The integration of AI tools in the field of language teaching and learning has expanded rapidly since advanced language models came into being. AI in language education has been helpful and will be quite promising. However, this promising fact presents both challenges and opportunities for TESOL practitioners in seeking to incorporate cutting-edge technology into their teaching approaches. Recent TESOL research studies have explored various applications of generative AI, providing personalized feedback to facilitate writing instruction. However, the specific application of key phrase extraction technologies for teaching fundamental language skills remains underdeveloped despite its significant potential. This paper will explore the theoretical foundations of key phrase extraction, examine the process of key phrases from the traditional method to the computational methods that underpin these technologies, and present practical strategies for implementing AI-driven key phrase extraction in the teaching of writing skills within TESOL contexts.

**2. Literature review**

**2.1 Key phrase extraction regarding semantic elements**

Key phrases can work as decisive indicators of central themes and ideas within texts, acting as linguistic signposts that guide readers and writers toward the most important information. In linguistics, semantics is defined as the study of meaning in language, focusing on how individual words and their combinations form meaningful sentences and convey complex ideas (Lyons, 1977). Semantic analysis delves into how people use language to communicate various types of information and emotions, distinguishing between connotational meanings, those that are implied or associated, and denotational meanings, which are the explicit, dictionary definitions of words (Garza-Cuarón, 2013).

For language learners, such as learners of English, especially those navigating the vast and often overwhelming landscape of digital content, the ability to identify and interpret key phrases is invaluable. Key phrases provide cognitive anchors that help learners of English quickly grasp the main ideas of a text, organize information, and construct meaning, which is particularly beneficial when processing large volumes of content such as academic articles, news stories, or social media posts (Scott, 1997). These key phrases not only enable understanding but also aid the construction of literacy proficiencies, including summarizing, analyzing, and synthesizing information (Baker, 2006). In electronic environments, key phrases are crucial for efficient information retrieval, allowing both human users and computer programs to find appropriate content quickly (Zhuhadar, 2015).

Nonetheless, key phrase identification is not without issues, given that it demands context sensitivity, cultural awareness, and appreciation of the dynamic nature of online language (Leppänen & Peuronen, 2012). Developments in natural language processing (NLP) and artificial intelligence (AI) have enabled the automation of key phrase identification, thereby assisting language learners in unpacking tricky texts and developing reading and writing proficiency (Kovács, Csépányi-Fürjes & Tewabe, 2023). It can be said that key phrase comprehension and utilization are central not just to semantic meaning but also to enabling learners to be more proficient and independent users of language in academic as well as real-life contexts (Crystal, 2001).

**2.2. The traditional method to key phrase extraction**

In the traditional method of key phrase extraction, the evaluation metrics used in determining the best model include Precision, Recall, F1-Score, and support. These measures were chosen carefully to enable a thorough investigation of the extraction performance of every algorithm (Sun et al., 2020).

**a. Accuracy**

Within the framework of observations or projections, accuracy is a variable that measures the percentage of correct predictions to the total number of predictions. It provides an overall assessment of a method’s integrity but does not distinguish among multiple types of error (Tayabali, 2020).

Accuracy (%) =

Where Correct Prediction contains both positive and negative cases (True Positive (TP) + True Negative (TN)) is accurately predicted and Total Predictions is the total of all forecasts, accurate and inaccurate (True Positive (TP) + True Negative (TN) + False Positive (FP) + False Negative (FN).

**b. Precision:**

Precision is a metric used in classification algorithms to evaluate how effectively a model recognizes positive cases. For instance, it estimates the number of “positive” projections which work can be proved to be reliable (Gupta et al., 2022).

Precision (%) =

**c. Recall:**

Recall is an achievement statistic that measures the ability of an algorithm to precisely identify each meaningful occurrence of a specific class. It refers to the true positive rate or sensitivity (Gupta et al., 2022).

Recall (%) =

**d. F1 Score:**

F1 score is the balanced average of Precision and Recall. F1 score can be utilized as a single parameter to examine a classification algorithm when an appropriate ratio among Precision and Recall. It is helpful to be used when the classes are unbalanced (Gupta et al., 2022).

F1-score (%) =

The variables true positive (TP), true negative (TN), false positive (FP), and false negative (FN) of each machine learning algorithm are represented by the following confusion matrices.

**Confusion matrix**

A Confusion matrix shows the variables true positive (TP), true negative (TN), false positive (FP), and false negative (FN) for each machine learning algorithm. This matrix provides a detailed breakdown of prediction outcomes and supports the calculation of all the above metrics (Tayabali, 2020).

**2.3. Computational approaches to key phrase extraction**

Finding important phrases has come a long way from manually to using advanced computer methods that make it possible to systematically and on a large scale extraction of semantically important terms. RAKE (Rapid Automatic Keyword Extraction) is the first statistical and rule-based method to mention because it uses statistical patterns to look at how often words appear and how they are used together in texts. It uses stop words as phrase delimiters to find meaningful multi-word phrases without using pre-trained data, which makes it useful for domain-specific applications (Manning & Schütze, 1999). RAKE works well and quickly with small or domain-specific datasets. It does not need outside corpora or pre-trained models, and it can find multi-word phrases using statistical co-occurrence. However, RAKE only provides frequency and co-occurrence. Moreover, to extract key phrases, RAKE must depend on the quality of stop word lists and overlooks infrequent terms. Another model which uses statistics is YAKE (Yet Another Keyword Extractor). It uses built-in text features like word cohesion to find key phrases. YAKE uses self-contained design and makes it easy to adapt to single-document analysis (Campos et al., 2018). Though YAKE does not need any external corpora or dictionaries, it can extract keywords from a single document and considers a number of intrinsic features, such as position and frequency. Since YAKE does not use outside knowledge or semantic context, it may not work well with documents that have strange structures.

Modern computer methods can now replace traditional rule-based methods for extracting key phrases. Models such as BERT and KeyBERT have revolutionized the field of semantic analysis by means of contextual embedding. These models capture more sophisticated language structure, including the meanings of words with more than one definition and representations for phrases that depend on left and right context. Hence, semantic search and summarization tasks become more precise (Kovács, Csépányi-Fürjes, & Tewabe, 2023). Because transformer-based models can comprehend arbitrary contexts and meanings in both directions, and because they get away with dealing with words that have many nuances of meaning, they can achieve strong performances on many NLP tasks. But they require a great deal of processing power and memory. They also require large, labeled data sets to perform well.

KeyBERT extends the application of BERT embeddings for capturing context in consolidating shallow word frequency and deep context relevance by identifying phrases that semantically similar to the document as a whole (Papagiannopoulou & Tsoumakas, 2020). KeyBERT retrieves keywords strongly semantically aligned with the document using BERT embeddings to obtain dense semantic similarity. KeyBERT is a bridge between frequency-driven and semantic-driven approaches. But it still relies on the biases and quality of BERT model.

These above methods can transform the extract of key phrases from a subjective, labor-intensive task into a replicable process. By combining statistical rigor, contextual embeddings, and unsupervised learning, they enable consistent application across diverse texts, from social media posts to academic papers, while addressing challenges like scalability and linguistic ambiguity highlighted in contemporary NLP research (Koroteev, 2021). From the discussion of the previous studies above, we choose KeyBERT as the top choice since it has a strong balance of performance and practicality with the accuracy of extraction is high and contextual understanding, though the speed is moderate.

**3. Implementing key phrase extraction for teaching writing skills**

KeyBERT is a machine learning model that extracts key phrases and keywords from text using BERT-based embeddings. In the context of teaching writing skills, KeyBERT can help students identify main ideas and supporting details in their writing, reflect on the focus and coherence of their texts, improve summarization and paraphrasing skills and enhance vocabulary by highlighting essential terms and phrases

The process of how KeyBERT works will be illustrated as follows.

* Input: A block of text (e.g., a student essay or paragraph).
* Embedding: The text is transformed into vector representations using BERT.
* Candidate Generation: KeyBERT generates candidate words or phrases (n-grams).
* Similarity Scoring: It calculates the cosine similarity between the document embedding and each candidate phrase.
* Output: The top-ranked keywords or key phrases that best represent the content

*Example:*

*Improving good writing skills is a difficult task. It needs much of students’* *effort, time and energy.* *Students can take online courses and have access to writing materials on the Internet. Learning writing skills steadily and trying to use them in many contexts are essential steps to address this issue.*

Input

# Initialize the model

kw\_model = KeyBERT()

# Input paragraph

text = (“Improving good writing skills is a difficult task.”

“It needs much of students’ effort, time and energy.”

“Students can take online courses and have access to writing materials on the Internet. “

“Learning writing skills steadily and trying to use them in many contexts are essential steps to address this issue.”)

# Extract key phrases

keywords=kw\_model.extract\_keywords(text,keyphrase\_ngram\_range=(1, 3), stop\_words='english', top\_n=5)

# Print results

for kw in keywords:

print(kw)

Expected Output:

(‘writing skills’, 0.785)

(‘online courses’, 0.645)

(‘improving good writing’, 0.632)

(‘students effort’, 0.610)

(‘learning writing skills’, 0.605)

**3.1 Developing coherent arguments through key phrases**

Key phrases are pivotal in writing, as they appear in essay titles, claims, and body paragraphs, emerging from selected evidence and analysis. These terms serve as the foundation to build and develop arguments (https://ielts.idp.com/uruguay/prepare/article-unlocking-success-power-keywords-phrases-task2). Teachers can help students identify and effectively develop key phrases that are important for enhancing their writing skills. By incorporating key phrases, students bridge different sections in their writing to ensure that their arguments flow logically and coherently. This coherence is to maintain the focus throughout an argumentative text and support claims with evidence. Key phrases also help students develop complex ideas by linking abstract concepts to tangible evidence. When students can write more coherently using key phrase extraction, they can also develop their analytical and critical thinking abilities. They can create well-structured arguments that can successfully communicate their intended messages, which are clear and cohesive.

**3.2 Reverse-engineering from key phrases**

In this activity, students are given a list of key phrases that were automatically extracted from a well-written example text (Khalifa & Albadawy, 2024). After that, students are given a task and are asked to use these important phrases to create their own paragraphs or essays. After students finish their drafts, they can examine how different approaches to develop ideas differ by comparing their work with the original text. Students can learn how to employ key phrases to organize arguments to be coherent and express the meaning of their writings by using the comparison. Students can learn about the flexibility of language and the significance of contextualization in writing by examining how authors use the same essential phrases to express ideas. This exercise can enhance students’ critical thinking, creativity, and writing skills while fostering their deep understanding of how key phrases contribute to the overall coherence and effectiveness of a text.

**3.3 Key phrase self-assessment**

Another effective activity to improve students’ writing abilities is to teach them how to use AI tools such as KeyBERT for key phrase extraction to assess their own writing drafts (Malik et al., 2023). Students can determine whether their writings can convey their ideas by utilizing these technologies. This helps them to identify any topical drift of key phrases, which can affect the coherence in their writings. When students can make sure that there are the main ideas in their writings, they can improve thematic coherence through the revision process. This process of self-evaluation can help them write more clearly and develop critical thinking skills. By actively engaging with AI-generated feedback, students can become more adept at evaluating their own writing and making targeted revisions to enhance its overall effectiveness. This approach also supports the development of autonomous study.

**4. Ethical considerations and challenges**

**4.1 Privacy and data security**

The extraction and analysis of data, especially personal data from online sources, raises privacy concerns1. When implementing AI-based key phrase extraction in educational settings, educators must ensure that student writing samples are processed securely, and data retention policies are transparent and appropriate, and the third-party AI services have clear privacy guarantees (https://www.dataguard.com/blog/growing-data-privacy-concerns-ai/).

* 1. **Bias and fairness**

Machine learning models for semantic analysis can inherit biases present in their training data1. This is particularly concerning in language teaching contexts where certain cultural expressions may be misinterpreted or undervalued; and non-standard English varieties might be incorrectly analyzed; and texts from marginalized perspectives might be processed differently. Teachers should critically evaluate how key phrase extraction technologies respond to diverse texts and supplement AI analysis with culturally responsive teaching approaches (Lewis, 2025).

**4.3 Balancing AI assistance and learner autonomy**

While AI-powered key phrase extraction offers valuable support, excessive reliance on AI could impede students’ development of independent analytical skills. Concerns regarding an excessive dependence on AI and the necessity for students to retain critical thinking abilities were brought to light by a recent systematic review on the use of AI in EFL writing instruction. To reduce this risk, English teachers should create tasks that gradually remove AI scaffolding, clearly explain the reasoning behind the identification of key phrases, and promote critical assessment of analyses produced by AI (Dwivedi et al., 2021; Lee et al., 2025)

**4.4 Future directions and recommendations**

Future research is expected to include multimodal information, that is, text analysis co-occurring with image, audio, and video in the potential applications of key phrase extraction for English language learning. This approach would give a core in context. Key phrase extraction can be used to identify patterns in students’ writing in order to focus on particular vocabulary and structural weaknesses or generate exercises with students’ interaction with phrases. Furthermore, keyword extraction should also be used to support individualized learning. Teachers also need to develop professionally by themselves with the purpose of obtaining technical proficiency in terms of basic tools of key phrase extraction as well as being ready to verify AI-generated analyses that are based on the key phrase extractions. Teachers need to employ pedagogical approaches in the implementation of these technologies, and ethical frameworks to ensure responsible use of key phrase extraction.

**5. Conclusion**

Key-phrase extraction technology developed using AI is now proving useful in instruction on writing for learners of English as a foreign language. Students can apprehend the semantic richness of writing resources with key phrase extraction technologies, which are able to detect key ideas and themes in a text automatically, with tools based on natural language processing models such as keyBERT. Thus, this enables students to organize their thoughts and write in a more logical manner.

From conventional to computational methods, the theoretical basis of key phrase extraction in semantic analysis may provide a good premise for educational content. These technologies are particularly relevant in the evolving space of language learning as they bridge the division between traditional keyword-based methods and more context aware semantic interpretation. Valuable pedagogical approaches such as scaffolded writing assignments, and transcriptions of comparative analysis between automatic and manual extraction of key phrases, and guided writing with key phrases extracted by AI are enabling the usage of the technologies in the extraction of key phrases in language instruction at different levels of English language proficiency among learners.

Furthermore, using AI-driven key phrase extraction does not reduce the importance of human roles in language instructions. Rather, it improves the effectiveness of language instructions by providing English language learners with personalized feedback and meaningful insights, while it also encourages critical thinking and learner autonomy. To prepare students for a future in which AI-based communication becomes more common, teachers can use key phrase extraction to address difficulties in language production and comprehension.

However, teachers should pay continuous attention to ethical issues like algorithmic bias and professional development in the application of AI-key phrase extraction. Teachers can design more effective and engaging language learning environments that meet the needs of English language learners through using AI-driven key phrase extraction in their English instruction.

**References**

1. Baker, P. (2006). *Using Corpora in Discourse Analysis*. Continuum.
2. Campos, R., Mangaravite, V., Pasquali, A., Jorge, A. M., Nunes, C., & Jatowt, A. (2018). Collection-Independent Automatic Keyword Extractor. *In Proceedings of the 10th ACM Conference on Web Science* (pp. 31-38).
3. Crystal, D. (2001). *Language and the Internet*. Cambridge University Press.
4. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, *57*, 101994.
5. Garza-Cuarón, B. (2013). *Connotation and meaning*. Walter de Gruyter.
6. Gupta, S., Saluja, K., Goyal, A., Vajpayee, A., & Tiwari, V. (2022). Comparing the performance of machine learning algorithms using estimated accuracy. *Measurement: Sensors*, *24*, 100432.
7. <https://ielts.idp.com/uruguay/prepare/article-unlocking-success-power-keywords-phrases-task2>
8. <https://www.dataguard.com/blog/growing-data-privacy-concerns-ai/>
9. Khalifa, M., & Albadawy, M. (2024). Using artificial intelligence in academic writing and research: An essential productivity tool. *Computer Methods and Programs in Biomedicine Update*, *5*, 100145.
10. Koroteev, M. (2021). BERT in Search: A Review of the Impact of BERT on Search Engines. *Journal of Intelligent Information Systems*, *57*(2), 257-275.
11. Kovács, L., Csépányi-Fürjes, L., & Tewabe, W. (2023, October). Transformer Models in Natural Language Processing. *In International Conference Interdisciplinarity in Engineering* (pp. 180-193). Cham: Springer Nature Switzerland.
12. Lee, S., Choe, H., Zou, D., & Jeon, J. (2025). Generative AI (GenAI) in the language classroom: A systematic review. *Interactive Learning Environments*, 1-25.
13. Leppänen, S., & Peuronen, S. (2012). *Multilingualism on the Internet*. The Routledge handbook of multilingualism, 384-402.
14. Lewis, A. A. (2025). Unpacking Cultural Bias in AI Language Learning Tools: An Analysis of Impacts and Strategies for Inclusion in Diverse Educational Settings. *International Journal of Research and Innovation in Social Science*, *9*(1), 1878-1892.
15. Lyons, J. (1977). *Semantics*. Cambridge University Press.
16. Malik, A. R., Pratiwi, Y., Andajani, K., Numertayasa, I. W., Suharti, S., & Darwis, A. (2023). Exploring artificial intelligence in academic essay: higher education student's perspective. *International Journal of Educational Research Open*, *5*, 100296.
17. Manning, C. D., & Schütze, H. (1999). *Foundations of Statistical Natural Language Processing*. MIT Press.
18. Papagiannopoulou, E., & Tsoumakas, G. (2020). KeyBERT: Keyphrase Extraction with BERT. *arXiv preprint arXiv*:2004.08716.
19. Scott, M. (1997). PC analysis of key words - and key key words. *System, 25*(2), 233-245.
20. Sun, C., Hu, L., Li, S., Li, T., Li, H., & Chi, L. (2020). A review of unsupervised keyphrase extraction methods using within-collection resources. *Symmetry*, *12*(11), 1864.
21. Tayabali, S. (2020). A simple guide to building a confusion matrix.
22. Zhuhadar, L. (2015). A synergistic strategy for combining thesaurus-based and corpus-based approaches in building ontology for multilingual search engines. *Computers in Human Behavior*, *51*, 1107-1115.