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Knowledge Graph-Based Intelligent Framework for English Language Learning Analytics

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Abstract: This research proposes the design of an innovative knowledge graph-based personalized learning approach to resolve problems associated with the rigid structure of English learning processes and content-oriented recommendation systems. This approach tries to integrate learner profiles, English subject connections, learning analytics, and adaptive recommendations in order to deliver continuous personalized learning paths. The framework consists of data acquisition, knowledge graph creation, learning analytics, and recommendation components. The data acquisition component includes information about studied topics, difficulty, preferences, test scores, task completion, and time spent. Knowledge of vocabulary, grammar, and reading subjects is defined as interrelated knowledge graph nodes. Learning analytics identifies learners' strong and weak aspects and recommends personalized learning activities accordingly. Classroom observations and before/after percentage comparisons were applied for the assessment of learning outcomes and teacher and learner feedbacks. Overall average learner's results improved from 48.4% prior to implementation to 81.0% after implementation, resulting in a 32.6 percentage point improvement. Vocabulary building improved from 48% to 82%, grammar understanding from 56% to 85%, reading confidence from 45% to 79%, writing practice motivation from 38% to 72%, and engagement from 55% to 87%. Average teacher and learner feedback increased from 51.0% to 85.3%, gaining 34.3 percentage points. The learner satisfaction score achieved 88%, and the recommendation relevancy had the highest increase in the feedback rate at 38 percentage points. The results suggest that combining knowledge graphs and learner analytics is capable of creating an interconnected, adaptive, and engaging English language learning environment without making teachers go through much effort in choosing lessons. The proposed model appears to be a potential supplement to rigid teaching, even though more research is required to verify its effectiveness.

Key Words: knowledge graph, personalized learning, english language learning, learning analytics, adaptive learning path, educational recommendation system, learner engagement

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Introduction

English is widely spoken around the world for educational and professional purposes, as well as in everyday interactions; therefore, schools and colleges consider this language very important. A traditional teaching method of English involves a definite order of covering material from the textbook, and it does not always correlate with the pace at which a learner grasps new vocabulary and grammatical patterns. Learners who use e-learning are confronted with an even greater challenge since there are no personal weaknesses assessed and addressed while using online platforms, as they present the same material to all users Huang & Zhu, (2021). As a result, some learners lose interest, while others find it too easy. A learning strategy that is aware of and considers the interrelated nature of the subject could benefit learners immensely (Qu et al., 2024).

A knowledge graph is a basic form for visualizing relations between various forms of knowledge. In an educational context, a knowledge graph allows one to incorporate words, grammatical aspects, reading subjects, and exercises as interconnected nodes, where the system would be able to recognize the topics, a learner is familiar with and those topics he or she should learn (Huang & Zhu, 2021). It makes it possible to construct a learning path instead of a static list of lessons. The latest research has proven that a knowledge graph allows a learner to move from simple topics to more complex one's step by step according to his/her personal progress and not just an approximate course developed for all students altogether (Zhou & Wang, 2025).

In learning analytics, learner activities are recorded, analyzed, and studied for things like completed modules, incorrect answers, and the time taken on each subject. Combining the data gathered with knowledge graphs provides an exact representation of what areas learners are weak and strong in, regarding English (Gao, 2025). Teachers generally lack the time to evaluate individual learners, especially in a classroom filled with many learners, and therefore using a system to automatically analyze learner data and provide relevant practice material will save them time as well as allow them to focus more on those learners in need of additional assistance. This can also be useful in identifying issues among all the learners in a batch (Xue, 2023).

The primary objective of this paper is to create a simplistic yet comprehensive architecture that utilizes a knowledge graph for assisting English language learning using learning analytics. This framework will help in collecting learner information, building a relational knowledge structure regarding English, analyzing the learner's performance, and giving personalized suggestions for further learning (Nguyen & Nguyen, 2024). This paper also describes all the components of the framework in a simplistic way, thereby making it easily comprehensible even to people who have no technological background and experience. A before-and-after comparison has been given to illustrate the practical value of such a framework.

- The research suggests an integrative approach that includes knowledge graph-based learner profiling, English content mapping, learning analytics, personalized learning path generation, and continuous feedback.
- The approach relates vocabulary, grammar, reading, and writing concepts to provide learning activities that are relevant and organized progressively for the individual learner.
- The approach helps engage learners and develop their language skills while allowing teachers to choose appropriate topics and create personalized learning activities.

Section 1 is where the background, problem, objectives, and contributions are provided. Related works are discussed in Section 2. In Section 3, the proposed framework is introduced, whereas the methodology section is presented in Section 4. Section 5 is about the findings, followed by discussion and limitations in Section 6. The conclusion is given in Section 7.

Literature Review

Knowledge Graph Based Recommendation Systems for Learning

A number of works have developed recommendation systems for English learning based on knowledge graphs. A personalized recommendation system for learning materials used a knowledge graph to connect learners' profiles to subject material and recommend learning material in accordance with learners' abilities Huang & Zhu, (2021). Also, there is research that developed a recommendation model

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for learning paths that is the combination of a knowledge graph and a decision-making process that guides learners gradually through subjects in accordance with their current level Zhou & Wang, (2025). In addition, another research study developed a web-based learning platform for English majors in which course material was represented in the form of a knowledge graph for the purpose of selecting a learning path in accordance with their interests and levels (Chen, 2025).

Knowledge Graph Application in English Teaching and Course Design

Knowledge graphs have also been used to facilitate teachers with the organization of English course content. For example, a teaching assistance system developed for English courses in college employed knowledge graphs to arrange topics in lesson preparation by teachers Gao, (2025). In addition, another research project has concentrated on developing a knowledge graph for language universities, integrating grammar, vocabulary, and communication skills topics using linguistic intelligence techniques (Wu, 2025). Moreover, there is research concerning English major online platforms, indicating that the representation of course content in graph form, rather than a simple listing of chapters, makes it easier to identify relations between topics for both teachers and learners (Chen, 2025).

Knowledge Graph-Based Learning Path Planning

One of the ways that knowledge graphs have been utilized is for the planning of a proper learning pathway for every individual learner. There is one learning path recommendation strategy that has utilized knowledge graph mining along with adaptive methods to guide the learners according to their past learning experience (Nguyen & Nguyen, 2024). Similarly, there is another strategy that is named Personal Learning Path Planning Strategy. This strategy has created a complete pipeline for creating a learning path right from the creation of the graph till the suggestion of the path. This was made for online learning platforms in such a way that the learning path could be modified according to the performance of the learner (Hou et al., 2025).

Knowledge Graph in Vocabulary and Language Skill Teaching

The vocabulary section is among the most difficult areas of the English language, and the use of knowledge graphs has been applied in order to make the vocabulary learning process more structured. One research study carried out in an adaptive learning platform utilized a knowledge graph in recommending English vocabulary exercises that would suit the learner's known and unknown vocabulary (Feng, 2025). In another research study, a knowledge graph structure was created in order to help language universities understand the connection between new vocabulary and the subjects being studied by those learning English as their second language (Wu, 2025).

Knowledge Graph Based Question Answering and Chatbot Systems

Question-answering tools and chatbots using knowledge graphs are also created to help learners directly. A question-answering tool developed using a knowledge graph of a high school course helped learners ask questions related to the course and obtain answers taken directly from the knowledge graph itself Yang et al., (2021). KBot is another example of a chatbot that used a knowledge graph with linked data to interpret questions asked by learners and provide appropriate answers without requiring rule-based scripts (Ait-Mlouk & Jiang, 2020). The examples show how a knowledge graph can be useful not only for recommendations but also for interacting directly with the learners.

Knowledge Graph Construction Techniques from Other Domains

However, there exist some practical knowledge graph creation approaches that originate from different fields and may also serve as a guideline when designing English learning graphs. For instance, an iron ore deposit analysis used text mining and deep learning to create a knowledge graph out of disorganized data (Qiu et al., 2023). Similarly, the study of Chinese intangible cultural heritage used domain ontology and natural language processing to create a knowledge graph among different cultural objects (Dou et al., 2018). These studies demonstrate a general approach to converting unstructured text and data into a knowledge graph that can also be employed while creating an English learning graph.

Reinforcement Learning Integration with Knowledge Graph

Reinforcement learning is usually coupled with knowledge graphs to create intelligent recommendations that get better through time. In the learning path simulation, a deep reinforcement learning approach was paired with a knowledge graph, allowing the model to adapt to feedback from the learner and improve its learning paths gradually (Zhou & Wang, 2025). Another survey focusing on the integration of reinforcement learning and knowledge graphs highlighted a number of ways to use both techniques together as well as potential future research avenues (Huo et al., 2024). Such a technique enables the learning system to constantly adapt its recommendations instead of applying the same static algorithm for all learners.

Research Gap

Despite extensive research into the usage of knowledge graphs for English learning, almost all of it is centered on just one part of the whole process, including only recommendations, or just vocabulary, or just path planning. Research into the effect of knowledge graph-based learning on student performance and experience identified the gap in the research, in which there is no clear framework that would incorporate all steps of the process from data collection to building a graph, analyzing, and making recommendations (Qu et al., 2024). The visual analysis of NLP trends in the field of education also identified the same gap, as almost all of the tools are explained in a highly technical way that does not suit the average teacher (Xue, 2023).

Proposed Framework

Overview of the Framework

The suggested architecture consists of four interconnected levels, which makes it possible to understand how the process starts from gathering information about the learner until generating a final recommendation. At the first level, information about the learner and learner activity is gathered. The second level constructs the knowledge graph of the English subject content, which includes vocabulary, grammar elements, topics, and other aspects. The third level analyzes the learner data in combination with the knowledge graph to determine strengths and weaknesses of the learner. The fourth level makes use of this analysis to generate an individual recommendation and learning pathway for the learner.

Data Collection Layer

In this layer, information about the performance of the learner is collected, which includes marks scored, answers to exercises, time devoted to each topic, and the topics avoided or reviewed by the learner. Information such as the class level of the learner and his/her favorite areas of interest is also collected in

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this layer. The information gathered in this layer is organized in an orderly way that helps to correlate it with the knowledge graph in the following layer. If there is no data collection layer, then the entire framework will fail to recognize the existing knowledge of the learner.

Knowledge Graph Construction Layer

At this stage, the content of English topics is decomposed into smaller components, such as a word, its meaning, use, and associated grammar rule. The techniques such as text mining and language processing, which are used to create graphs for other subjects' content, are utilized in this case as well to arrange English content in nodes and edges (Qiu et al., 2023; Dou et al., 2018). The connectivity of this structure enables the system to recognize, for example, that the topic of grammar is related to some words and passages of reading, and not as independent pieces of information.

Learning Analytics Layer

It analyzes the information about the learner that has been acquired in the previous layer along with the knowledge graph in order to determine the learner's current level in various aspects of English such as vocabulary, grammar, reading, and writing. It determines which linked items have been covered by the learner and which of them require further work. It is like an evaluation layer, providing a snapshot of the current level of the learner before recommending any new material, thereby avoiding repetitive and irrelevant practices for the learner.

Personalized Recommendation Layer

According to the output obtained from the analytics layer, the current layer makes a choice of the most appropriate next topic, word list, or exercise for the learner out of the knowledge graph (Huang & Zhu, 2021). It creates a learning path consisting of several steps, not one big list of tasks, which allows the learner to go through tasks gradually. Based on the information about the new performance obtained in the process of accomplishing tasks, the system makes a modification of the learning path (Nguyen & Nguyen, 2024). The following table 1 presents a brief description of all the layers of the framework and their functions.

Table 1: Layers of the Proposed Framework and Their Function

Framework Layer	Main Function	Example Activity
Data Collection Layer	Collects learner activity, scores, and profile details	Recording quiz answers and time spent
Knowledge Graph Construction Layer	Organizes English topics into connected nodes	Linking a word to its grammar rule
Learning Analytics Layer	Studies learner data to find strong and weak areas	Checking completed and repeated topics
Personalized Recommendation Layer	Suggests next topic or practice for the learner	Giving a short vocabulary practice list

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Working Methodology

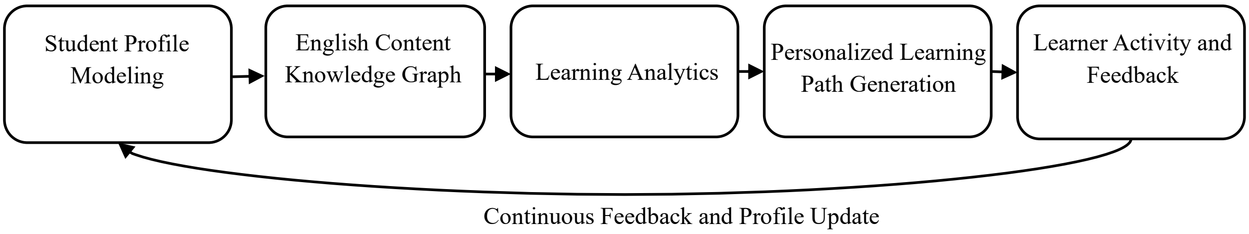

Figure 1: Workflow of the Knowledge-Graph-Based Adaptive Learning Framework

Workflow of knowledge-graph-based adaptive learning system is presented in the figure 1. First, the student's profile is generated, and English language materials are structured in the knowledge graph. Analysis of learner data helps to identify strengths and weaknesses, and the personalized learning path can be built. Performance of learners, which is recorded during their training, constantly refines the profile and recommendations.

Student Profile Modeling

Each user of the framework is provided with a profile containing basic information like class level, previously covered English lessons, and difficult areas for the learner. This profile gets updated continually as the user uses the framework. This profile serves as a basis for the entire framework, as the recommendation layer of the framework always considers this profile before recommending any lesson or practice material to the learner.

Mapping English Content to Knowledge Graph

The English subject content, which includes grammar rules, vocabulary words, and reading texts, is represented in the form of a knowledge graph by associating different items Wu, (2025). For instance, an English grammar rule of the past tense is associated with examples that use this grammar rule and commonly occurring words used along with this rule. This representation is done only once for the entire content of the subject, and whenever any new content is introduced, it continues to grow (Xue, 2023).

Learning Path Generation Process

After the creation of the learner profile and the knowledge graph, the framework proceeds in a sequential fashion through the connected nodes and selects topics that the learner has not mastered before but are connected with the topics that the learner has already mastered (Hou et al., 2025). It helps in creating a gradual learning curve and does not make the learner abruptly move on to a more difficult topic. This process continues even after each learning session so that the learning path continues to change according to the performance of the learner Zhou & Wang, (2025).

Feedback and Continuous Update Mechanism

The feedback is generated by the system when the learner has completed any recommended task and is then input back to the framework. This will help to modify the learner profile as well as slightly altering the perception of the framework of the strength and weaknesses of the learner (Qu et al., 2024). This process of constant modification helps to refine the suggestions further in a way that the process of reinforcement improves recommendations on the basis of past results (Huo et al., 2024). This is the process that makes the framework relevant even after a period of time.

Results and Discussion

Learning Engagement Before and After Using the Framework

The effectiveness of the framework was tested in the form of an observational study of the level of learner engagement before and after applying the framework in a classroom environment. The results showed that without the framework, learners would go through the lessons in a predefined order, and many of them found some lessons too easy whereas other lessons too difficult. Using the framework, lessons and practice exercises appeared better tailored to individual learner needs and more learners were motivated to learn. This is demonstrated in table 2.

Table 2: Percentage Comparison of Learner Engagement Before and After Using the Framework

Learning Area	Before Using Framework (%)	After Using Framework (%)	Improvement (%)
Vocabulary Building	48	82	34
Grammar Understanding	56	85	29
Reading Confidence	45	79	34
Writing Practice Interest	38	72	34
Overall, Class Engagement	55	87	32
Average	**48.4**	**81.0**	**32.6**

The results presented in table 2 show the significant improvement of all analyzed areas of learning after the introduction of the suggested approach. The average level of learner performance rose from 48.4% prior to the implementation to 81% afterward, which is an overall increase of 32.6 percentage points. Class engagement showed the highest post-implementation rate at 87%, whereas grammar comprehension was rated second at 85%. Learner vocabulary development grew from 48% to 82%, and reading self-confidence – from 45% to 79%. Writing practice interest also experienced significant improvement, going up from 38% to 72%.

Vocabulary and Grammar Improvement Observation

The learners who employed the recommended framework for activities of vocabulary and grammar exhibited improvement in several linguistic competencies. For vocabulary acquisition, there was an increase in word recognition competence from 51% to 84%, vocabulary retention from 46% to 81%, and contextual word usage from 43% to 78%. This shows that there was an improvement in the use of the newly acquired words in an appropriate context. In grammar acquisition, there was improvement in grammar rules identification from 55% to 86%, sentence construction from 49% to 82%, and grammatical errors identification and correction from 47% to 80%. This improvement was due to the fact that the knowledge graph enabled connections between familiar linguistic concepts and other more difficult ones. Instead of having unrelated exercises, the learners had their learning process organized in relation to their past performances and needs. As illustrated in figure 2, there was an increase of 31 to 35 percent in all vocabulary and grammar indicators.

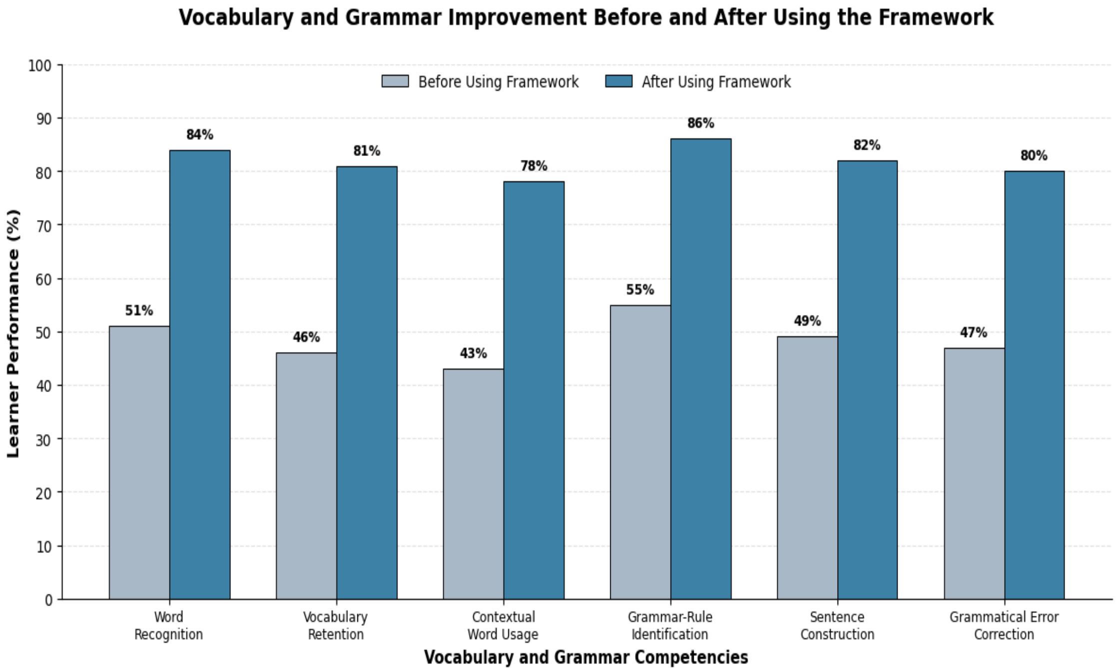

Figure 2: Percentage Improvement in Vocabulary and Grammar Competencies Before and After Using the Framework

Teacher and Learner Feedback Observation

The teachers who helped learners use the framework stated that they spent less time deciding on the next subject matter, as the framework had a suggested subject matter for each learner. The learners too said that the learning materials had become more cohesive in nature, shifting from one relevant subject matter to the other rather than hopping from one irrelevant chapter to another. Both the teachers and learners agreed that this coherent approach to learning, which is based on a knowledge graph, was more organized than the previous fixed lesson plan (Gao, 2025).

Table 3: Teacher and Learner Feedback on the Proposed Framework

Feedback Indicator	**Before Framework (%)**	**After Framework (%)**	**Improvement (Percentage Points)**
Efficiency in Selecting the Next Topic	50	83	33
Relevance of Recommended Topics	46	84	38
Connection Between Learning Materials	49	86	37
Organization of Daily Study Sessions	52	86	34
Teacher Satisfaction	55	85	30
Learner Satisfaction	54	88	34
Overall Average	**51.0**	**85.3**	**34.3**

Table 3 reveals that there was an improvement in teacher and student feedback for all evaluated parameters through the implementation of the suggested framework. The overall feedback rating showed a rise from 51.0% to 85.3%, which is an improvement of 34.3%. Student satisfaction rated the highest mark at 88%, whereas topic relevance witnessed the greatest improvement by 38%. This suggests that the framework helped teachers in reducing lesson planning time and offering students a more relevant and organized learning experience.

Discussion

There was an improvement in all the aspects associated with the learning of English based on the knowledge graph-based learning framework. The average performance of the learners went up from 48.4% prior to the use of the framework to 81.0% after its introduction. There was a boost in vocabulary development from 48% to 82%, comprehension of grammatical elements from 56% to 85%, reading ability from 45% to 79%, motivation for writing from 38% to 72%, and overall engagement from 55% to 87%. Teacher and learner responses went up from 51.0% to 85.3%, whereas learner satisfaction stood at 88% and there was a 38-percentage point improvement in recommendation relevance. These improvements show that there is a positive correlation between learner profile data, connections between English content, learning analytics, and recommendations for personalized actions. This framework enables instructors to minimize their effort when choosing lessons and learners to have structured, adaptable, and interactive lessons. This makes it an excellent alternative to the existing lesson plan and the recommendation system. The results were arrived at by observing classes and comparing percentages. They do not prove statistical significance, learning retention, causal relationships, or generalization to other educational facilities, age groups, language abilities, and learning environments. There is also a need for more information regarding the sample size, test reliability, and period of implementation. Future research should use large and diversified samples, reliable test instruments, control groups, and long-term experiments. The measures of statistical significance and effect sizes should be determined, as well as comparisons between traditional, adaptable, and non-graphical learning platforms.

Conclusion

The research attempted to solve the issue of rigid English learning pathways and independent recommendation systems, which neglect the aspect of individual performance, interlinked knowledge, and evolving needs. In order to solve this issue, the study proposed a knowledge graph-based personalized learning model that included the collection of learner information, mapping of English material, learning analytics, adaptive pathway creation, and continuous feedback. The results of the study show that the framework was helpful in bringing changes. Average learner performance went up from 48.4% to 81.0%, providing for a 32.6 percentage point increase. Vocabulary acquisition increased from 48% to 82%, grammar knowledge from 56% to 85%, reading confidence from 45% to 79%, interest in writing practice from 38% to 72%, and overall class participation from 55% to 87%. Teacher and learner feedback increased from 51.0% to 85.3%, which provided for a 34.3 percentage point increase. The rate of learner satisfaction attained 88% while the level of relevance of suggested topics made the most significant advancement in feedback with 38 percentage points. From all this, one can conclude that integration of knowledge graphs together with learner analytics results in creation of more relevant, connected and adaptive English learning experience. The major message from the study is that the process of personalized learning improves learner engagement and language acquisition at the same time as minimizing efforts for lesson selection for teachers.

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