Position: LLMs Can be Good Tutors in English Education

Anonymous ACL submission

Abstract

While recent efforts have begun integrating large language models (LLMs) into English education, they often rely on traditional approaches to learning tasks without fully embracing educational methodologies, thus lacking adaptability to language learning. To address this gap, we argue that **LLMs have the potential to serve as effective tutors in English Education**. Specifically, LLMs can play three critical roles: (1) as *data enhancers*, improving the creation of learning materials or serving as student simulations; (2) as *task predictors*, serving as learner assessment or optimizing learning pathway; and (3) as *agents*, enabling personalized and inclusive education. We encourage interdisciplinary research to explore these roles, fostering innovation while addressing challenges and risks, ultimately advancing English Education through the thoughtful integration of LLMs.

1 Introduction

English Education has long been a cornerstone of global education and a critical component of K-12 curricula, equipping students with the linguistic and cultural competencies necessary for an interconnected world (Alhusaiyan, 2025; Katinskaia, 2025). However, traditional English teaching methods often fall short in addressing the diverse needs of learners (Hou, 2020). Challenges such as limited personalization, scalability constraints, and the lack of real-time feedback are particularly pronounced in large classroom settings (Ehrenberg et al., 2001). Addressing these shortcomings requires innovative approaches that not only enhance the quality of instruction but also adapt to the unique learning trajectories of students (Eaton, 2010).

Recently, the advent of LLMs has opened new possibilities for transforming English Education (Caines et al., 2023). LLMs exhibit remarkable natural language understanding and generation capabilities, making them promising candidates for roles traditionally filled by human tutors. Leveraging LLMs as AI tutors can overcome inherent limitations of conventional teaching methods, offering scalable, interactive, and personalized learning experiences (Chen et al., 2024; Schmucker et al., 2024). Therefore, this position paper argues that **LLMs can be effective tutors in English education, complementing human expertise and addressing key limitations of traditional methods**.

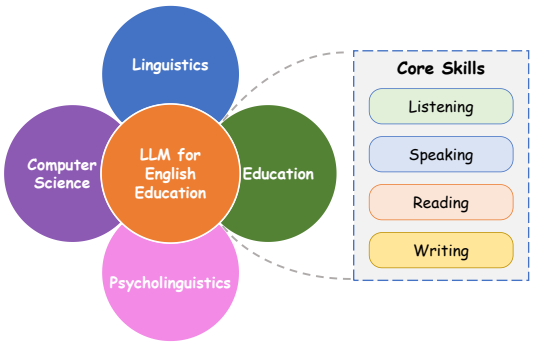

Figure 1: Involved disciplines of LLM for English Edu.

As shown in Figure 1, English Education intersects with multiple *disciplines*, each of which underscores the potential of LLMs to revolutionize this domain. From the perspective of (1) *computer science*, advancements in machine learning and NLP have enabled LLMs to process and generate human-like language at an unprecedented scale; (2) *linguistics* (Radford et al., 2009) contributes a deeper understanding of grammar, phonetics, and semantics, allowing LLMs to generate accurate and understandable language outputs; (3) *education* provides the foundation for designing effective pedagogical strategies, ensuring that LLMs can deliver personalized, engaging, and developmentally appropriate learning experiences; and finally, (4) *psycholinguistics* (Steinberg and Sciarini, 2013) bridges the gap between language acquisition and cognitive processes, enabling LLMs to optimize learner interactions by adapting to individual needs and fostering meaningful engagement. Together,

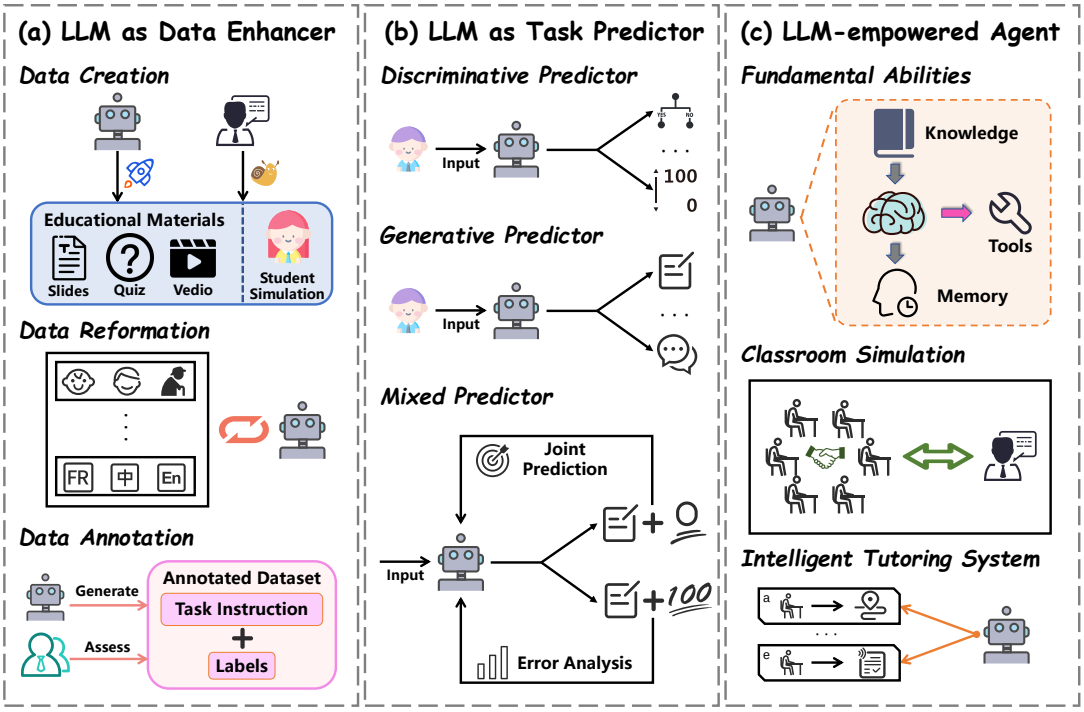

Figure 2: Overview of three roles of LLMs in English education. An overview of related literature is provided in Appendix A.

these disciplines position LLMs as uniquely capable of addressing the multifaceted challenges of English education.

Moreover, English Education encompasses four *core skills*: listening, speaking, reading, and writing, each of which can be significantly enhanced by LLMs. For listening, LLMs can generate diverse audio materials (Ghosal et al., 2023) and facilitate interactive voice-based exercises, helping learners improve their ability to discern pronunciation, intonation, and contextual meaning. In speaking, LLMs can simulate realistic conversations (Siyan et al., 2024), provide pronunciation feedback, and scaffold learners' oral communication skills through iterative practice. For reading, LLMs can curate leveled texts, generate comprehension questions (Samuel et al., 2024), and engage learners in discussions that deepen their understanding of written content. Finally, in writing, LLMs can offer real-time grammar, syntax, and style feedback while assisting with idea generation and iterative revisions (Stahl et al., 2024a). By addressing these core skills holistically, LLMs have the potential to deliver a comprehensive and adaptive learning experience.

Despite these opportunities, the deployment of LLMs in English Education must be approached carefully, ensuring that their integration complements rather than replaces human tutors (Jeon and Lee, 2023). As illustrated in Figure 2, this paper explores three critical *roles of LLMs* in this context: their function as ***data enhancers*** (Section 4) to optimize learning materials, their capacity as ***task predictors*** (Section 5) to tailor educational solutions, and their potential as ***agents*** (Section 6) that deliver interactive and adaptive language instruction. By examining these roles, we aim to demonstrate how LLMs can address the limitations of traditional English teaching methods while advancing our understanding of intelligent tutoring systems. Additionally, we discuss potential challenges, ethical considerations, and future directions (Appendix C) for integrating LLMs into English Education, offering a technical guideline for researchers and educators to harness their transformative potential. We also describe the paradigm shift of leveraging AI for English Education, starting from the last century, as one of our contributions in Section 3.

2 Background

2.1 English Education

Traditional English Education methods often emphasize grammar rules, vocabulary memorization, and repetitive practice, supplemented by limited opportunities for real-world application (Watzke, 2003). Such approaches are often constrained by

the availability of skilled teachers, the diversity of learners' needs, and the lack of personalized feedback (Williams et al., 2004). Recently, many technologies for English Education have been proposed (Alhusaiyan, 2024), focusing on solving specific tasks instead of describing the whole picture of English tutoring. While intelligent language tutoring systems have the potential to create adaptive environments, attention to this field is relatively less compared to other subjects like science (Shao et al., 2025) and mathematics (Ahn et al., 2024). One key reason lies in the inherent complexity of language as an *ill-defined* domain (Schmidt and Strasser, 2022), posing a great challenge in establishing a valid automatic analysis of learner languages due to the vast variability and unpredictability of human language.

2.2 Large Language Models for Education

The potential of LLMs in education (Alhafni et al., 2024), particularly in English Education (Gao et al., 2024; Karataş et al., 2024; Cherednichenko et al., 2024), is immense. Benefiting from large-scale pretraining on extensive corpora, LLMs have demonstrated emergent abilities including (1) *in-context learning* (Dong et al., 2022), which allows the model to adapt to new tasks and provide contextually relevant responses based on a few examples provided during the interaction; (2) *instruction following* (Zeng et al., 2024), which enables the model to process and execute complex user instructions with high accuracy; and (3) *reasoning and planning* (Huang et al., 2024b), which allows the model to generate coherent, structured, and context-aware outputs, even for tasks that require multi-step thinking. However, these fundamental capabilities, while impressive, are insufficient to fully meet the unique demands of English Education. Teaching English requires more than generating grammatically correct sentences or providing accurate translations; it demands a nuanced understanding of pedagogy, learner psychology, and cultural context. Maurya et al. (2024) propose an evaluation taxonomy that identifies eight critical dimensions for assessing AI tutors. These dimensions can be broadly categorized into two groups. (1) *Problem-solving abilities* assess the technical capabilities of LLMs to perform tasks relevant to English Education. (2) *Pedagogical alignment abilities* evaluate how well the LLM aligns with effective teaching and learning principles. Pedagogical alignment includes the model's ability to adapt to the learner's proficiency level, provide scaffolded feedback, foster engagement, and maintain motivation. While LLMs can give direct answers, their ability to replicate these nuanced teaching strategies remains a challenge (Wang et al., 2024a).

3 Paradigm Shift

The development of AI models for English Education can be broadly categorized into four successive generations as shown in Figure 3: (1) *rule-based models*, (2) *statistical models*, (3) *neural models*, and (4) *large language models*. We leave the detailed description in Appendix B.

Our position. We foresee next-generation LLMs with deeper alignment to pedagogical principles and stronger guardrails to mitigate misinformation and bias. Future models may integrate multimodal data (e.g., text, image, video, speech) to adapt to diverse learner profiles in real time. These improvements will reinforce the position that LLMs can evolve into more effective tutors for English Education.

4 LLMs as Data Enhancers

Education is a high-stake area where any hallucination could cause devastating harm to humans' cognition activities (Ho et al., 2024). One of the hallucination causes is from data (Huang et al., 2023). Therefore, high-quality and diverse data resources (Long et al., 2024) are critical to ensuring the reliability of incorporating LLMs into English Education. The 1) *creation*, 2) *reformation*, and 3) *annotation* of educational materials are crucial to delivering effective and engaging teaching. Traditional resource development methods often lack the scalability, adaptability, and personalization necessary to meet the diverse needs of learners (Feng et al., 2021; Shorten et al., 2021). In contrast, LLMs emerge as transformative tools capable of enhancing these processes (Wang et al., 2024c; Liu et al., 2024c). This section explores how LLMs serve as data enhancers in English Education.

4.1 Data Creation

Creating pedagogically sound and learner-specific data is a cornerstone of personalized learning. However, manually creating such resources is time-consuming and often fails to address the wide range of learner needs (Cochran et al., 2022). LLMs can revolutionize this process by generating tailored

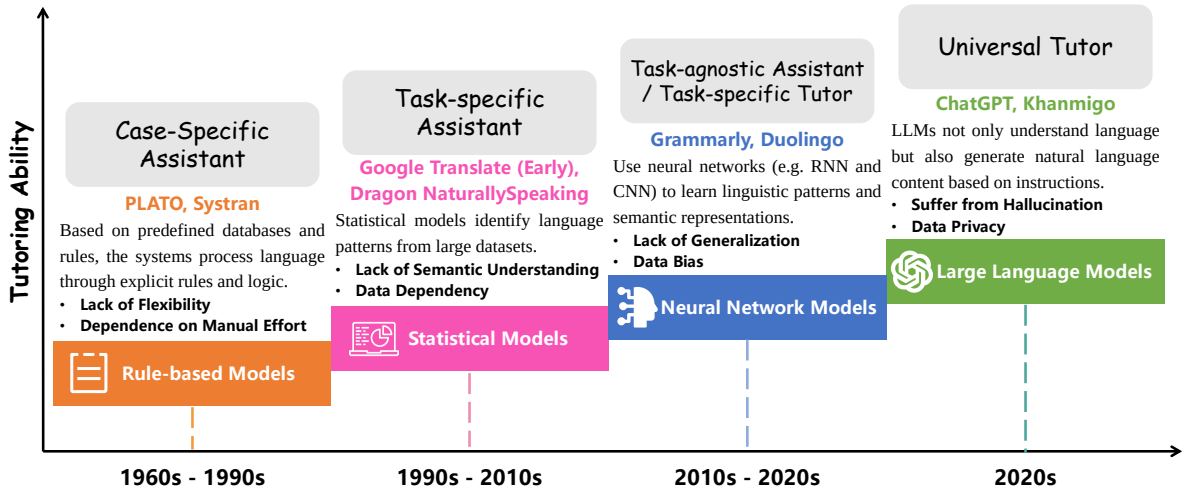

Figure 3: Roadmap of English Education.

and diverse educational content or responses on demand (Zha et al., 2023; Cochran et al., 2023).

Educational Materials Generation. A primary use of LLMs in data creation is the *generation of educational questions* aligned with specific learning objectives. Due to their superior contextual understanding, classic rule-based approaches have largely been eclipsed by neural network-based techniques (Kurdi et al., 2020; Rathod et al., 2022; Mulla and Gharpure, 2023). LLMs can produce answer-aware (whose target answer is known) or answer-agnostic (whose answer is open) (Zhang et al., 2021), resulting in more nuanced exercises and assessments (Xiao et al., 2023).

Student Simulation. Simulating the learner's perspective is crucial for designing adaptive instructional materials. Traditional surveys and standardized tests often fail to capture the complexity of dynamic learner behaviors (Käser and Alexandron, 2024). In contrast, LLM-based approaches enable high-fidelity, context-aware *student simulations* (Liu et al., 2024d; Yue et al., 2024), generating synthetic learners who exhibit realistic mastery levels and evolving behaviors. For instance, *Generative Students* (Lu and Wang, 2024) create simulated learners with various competency levels, while *EduAgent* (Xu et al., 2024) integrates cognitive priors to model complex learning trajectories and behaviors better.

Discussion. While LLMs excel at generating educational content, current approaches mainly focus on question creation, leaving many areas of English Education underexplored. Essential tasks like generating culturally rich reading materials, context-dependent writing prompts, or dynamic comprehension exercises still lack diversity and depth. Additionally, the student simulations created by LLMs often fail to reflect long-term learning trajectories or the intricacies of individual learning progress.

4.2 Data Reformation

In addition to creating new content, LLMs can adapt *existing* materials to better align with current needs. This process, commonly referred to as data reformation, involves (1) changing data types or modalities, (2) paraphrasing materials to match learner proficiency, and (3) enriching raw data with auxiliary signals or contextual content.

Teaching Material Transformation. Transforming existing materials into different forms can yield more comprehensive and immersive learning experiences. For example, *Book2Dial*(Wang et al., 2024b) generates teacher-student dialogues grounded in textbooks, keeping the content both relevant and informative. Their approach includes multi-turn question generation and answering(Kim et al., 2022), dialogue inpainting (Dai et al., 2022), and role-playing. Likewise, *Slide2Lecture* (Zhang-Li et al., 2024) automatically converts lecture slides into structured teaching agendas, enabling interactive follow-up and deeper learner engagement.

Simplification and Paraphrasing. Another vital application is simplifying or paraphrasing complex texts to specified readability levels (Huang et al., 2024a) without losing key concepts (Al-Thanyyan and Azmi, 2021). This is particularly beneficial in English Education settings, where language beginners often face advanced vocabulary and complex

structures (Day et al., 2025). Recent advancements in controllable generation (Zhang et al., 2023) leverage model fine-tuning on curated datasets (Zeng et al., 2023) or decoding-time interventions (Liang et al., 2024), thereby allowing educators to specify text complexity, style, or tone.

Cultural Context Adaptation. Beyond linguistic correctness, cultural nuance is another crucial factor in English Education (Byram, 1989, 2008). LLMs can facilitate this process by recontextualizing existing materials to reflect the cultural and social norms of different areas (Liu et al., 2024a; Adilazuarda et al., 2024; Kharchenko et al., 2024). For instance, a short story originally set in an English-speaking environment may be adapted for Japanese students by adjusting the characters' names, idiomatic expressions, or social customs, while preserving core instructional goals. This cultural adaptation not only enhances learner engagement but also strengthens cross-cultural competencies.

Discussion. While LLM-based data reformation can significantly enhance English Education, several gaps warrant attention. Most current studies prioritize textual forms or single-modal approaches, which may overlook valuable *multimodal* resources such as interactive video and audio-based content (Ghosal et al., 2023). Furthermore, cultural adaptation, although promising, remains underexplored in practical classroom scenarios, particularly for underrepresented persons and culturally sensitive topics. AlKhamissi et al. (2024) demonstrate how cultural misalignment can increase bias. However, robust empirical *evaluations* are still limited across diverse learners and linguistic backgrounds.

4.3 Data Annotation

While *Data Creation* focuses on generating learner-specific data, it often prioritizes diversity and adaptability over precision. The approach is particularly useful for tasks with large label spaces (Ding et al., 2024). In contrast, *Data Annotation* emphasizes producing high-quality, meticulously labeled data that is essential for tasks requiring accuracy and consistency. Unlike data creation, annotated data often undergoes rigorous validation to ensure its accuracy and relevancy (Artemova et al., 2024).

Annotation Generation. LLMs can be central to generating a variety of annotations, including categorical labels, rationales, pedagogical feedback, and linguistic features such as discourse relations. Recent prompt engineering and fine-tuning techniques have further expanded LLMs' annotation capabilities. For instance, Ye et al. (2024) leverage GPT-4 to annotate structured explanations for Chinese grammatical error correction, while Samuel et al. (2024) examine GPT-4 as a surrogate for human annotators in low-resource reading comprehension tasks. Likewise, Siyan et al. (2024) deploy GPT-4-Turbo for audio transcript annotations. However, inconsistencies across LLMs (Törnberg, 2024) remain a serious challenge, posing risks to educational reliability.

Annotation Assessment. Although LLM-based annotation is efficient, it also raises critical issues of bias, calibration, and validity, particularly in low-resource language contexts (Bhat and Varma, 2023; Jadhav et al., 2024). Automated or semi-automated evaluation strategies have emerged to address these quality concerns. For example, LLMs-as-Judges (Li et al., 2024a,b; Gu et al., 2024) reduce human overhead by automating evaluation, an approach increasingly explored in education-focused applications (Chiang et al., 2024; Zhou et al., 2024). However, purely automated frameworks can still propagate errors or bias.

Discussion. Although LLMs provide efficient data annotation, the inconsistency across different models remains a critical concern, affecting the quality and reliability of annotated educational materials. These discrepancies hinder the creation of universally reliable educational content, especially in diverse linguistic and cultural contexts. Additionally, automated annotations often lack the nuance needed for pedagogical applications, making it essential to involve human oversight in critical cases to mitigate errors or biases.

Our position. We acknowledge the current limitations in LLM-based data creation, reformation, and annotation for English Education. However, we believe that with continued interdisciplinary collaboration, these challenges can be addressed. *Future advancements* should focus on enhancing the accuracy and diversity of generated content, improving multi-modal and culturally sensitive learning materials, and integrating more robust systems for human-LLM collaboration (Li et al., 2023; Wang et al., 2024e) in data annotation. This will ensure that LLMs can fully realize their potential as effective tutors in English Education.

5 LLMs as Task Predictors

Task-Based Language Learning (TBLL) (Nunan, 1989; Willis, 2021) as a methodological approach is one of the effective English Education methods. LLMs have demonstrated remarkable capabilities in understanding and generating human language, making them well-suited for addressing numerous tasks in English Education. These tasks can be broadly categorized into three types based on their nature and the role of LLMs: 1) *Discriminative*, 2) *Generative*, and 3) *Mixed* of the above two roles.

5.1 Discriminative Task Predictors

Discriminative tasks in English Education primarily involve classifying learner inputs or grading their future performance. Below are some applications that are still calling for improvements:

Automated Assessment. The task aims to automatically grade students' assignments, including essay scoring (Seßler et al., 2024; Li and Liu, 2024; Syamkumar et al., 2024), short answer grading (Schneider et al., 2023; Henkel et al., 2024), and spoken language evaluation (Gao et al., 2023; Fu et al., 2024). LLMs can process learners' submissions to judge grammar, lexical diversity, coherence, and even spoken fluency, providing instant feedback. This scalability is particularly appealing for large classes, where human evaluators are often overwhelmed and unable to provide timely, personalized critique (Mizumoto and Eguchi, 2023).

Knowledge Tracing. Given sequences of learning interactions in online learning systems, Knowledge Tracing identifies and tracks students' evolving mastery of target skills (Shen et al., 2024b; Xu et al., 2023). LLM-based methods of Knowledge Tracing have been explored in cold-start scenarios (Zhan et al., 2024; Jung et al., 2024), offering strong generalization by inferring latent learner states from limited data. These approaches can support adaptive learning pathways, giving personalized recommendations based on predicted performance and knowledge gaps.

Discussion. Despite their promise in automating and personalizing these discriminative tasks, LLMs still grapple with notable limitations that hinder their utility as robust tutoring tools. First, *misalignment of assessment with expert instructors* poses risks: machine-generated scores may deviate from established rubrics or neglect qualitative nuances, leading to potential discrepancies in grading quality (Kundu and Barbosa, 2024). Second, the *lack of empathy* compounds this issue, as assessments devoid of human judgment risk discouraging learners or overlooking subtle motivational factors (Sharma et al., 2024). Knowledge tracing approaches, while promising in cold-start scenarios, struggle with capturing the complexity of long-term learning trajectories and deeper cognitive processes (Cho et al., 2024). These concerns point to the need for more transparent and human-centered methods in utilizing LLMs for assessment.

5.2 Generative Task Predictors

Generative tasks involve producing new content or responses. LLMs are known to be adept at these tasks due to their generation capabilities.

Grammatical Error Correction and Explanation. In English writing, errors often reveal learners' gaps in grammar and vocabulary (Hyland and Hyland, 2006). LLMs can detect and correct these errors (Bryant et al., 2023; Ye et al., 2023), offering concise explanations (Ye et al., 2024) that reinforce language rules. By streamlining error detection and corrections, learners deepen their linguistic understanding.

Feedback Generation. Quizzes and exercises remain vital in English Education for practice and targeted remediation (Rashov, 2024). LLMs enhance this process by delivering prompt, personalized feedback that pinpoints strengths and addresses weaknesses (Borges et al., 2024). This scalability enables learners to self-regulate and refine their skills without relying solely on human graders (Stamper et al., 2024).

Socratic Dialogue. Moving beyond straightforward Q&A, Socratic questioning promotes critical thinking and self-reflection (Paul and Elder, 2007). *SocraticLM* (Liu et al., 2024b), for example, aligns an LLM with open-ended, inquiry-based teaching principles, guiding learners through iterative exploration rather than prescriptive correction. In theory, this fosters deeper conceptual understanding and active learner engagement.

Discussion. Despite the promise of LLM-based generation in English Education, multiple uncertainties persist. *Determining how to provide automatic feedback that genuinely maximizes learning outcomes* is an ongoing challenge (Stamper et al., 2024), particularly given education's risk-averse

culture and high accountability standards (Xiao et al., 2024). Moreover, while LLMs like SocraticLM have demonstrated success in domains like mathematics, their applicability to English Education contexts has not been thoroughly validated (Liu et al., 2024b). As such, the design of strategies and follow-up queries remains an open question in ensuring these systems track and respond to learners' cognitive states.

5.3 Mixed Task Predictors

Mixed tasks integrate discriminative and generative elements, requiring LLMs to evaluate learner inputs and generate meaningful feedback or suggestions. These tasks are particularly valuable in fostering an interactive and adaptive learning experience, as they bridge the gap between evaluation and instruction.

Automated Assessment with Feedback. While discriminative systems for automated essay scoring and speech evaluation primarily focus on assigning grades, LLMs extend these capabilities by simultaneously generating formative feedback (Katuka et al., 2024; Stahl et al., 2024b). For example, an LLM can evaluate the coherence and lexical diversity of a written essay, then offer specific revision strategies. In speaking practice, it can measure fluency and pronunciation accuracy while suggesting drills to refine intonation or stress patterns. Through this combination of scoring and tailored advice, learners gain a deeper understanding of their strengths and areas for improvement.

Error Analysis. Error Analysis systematically uncovers and categorizes learners' missteps, from syntactic lapses in writing to flawed pronunciations in speaking (James, 2013; Erdoğan, 2005). LLMs functioning in a mixed capacity can classify these errors and generate corrective guidance, providing revised sentences, clarifications of grammatical rules, or remediation exercises for identified weaknesses (Myles, 2002; Mashoor and Abdullah, 2020). Such insight facilitates targeted interventions that enhance language proficiency across modalities, including reading and listening.

Discussion. Mixed-task systems hold promise by combining assessment and feedback generation, but they face notable challenges. One major issue is the *weak alignment* between scoring mechanisms and the quality of feedback provided (Stahl et al., 2024b). For example, while essay scoring systems may deliver comprehensive evaluations, the feedback often lacks specificity, limiting its instructional value. Additionally, although error analysis has potential, *the absence of standardized pedagogical benchmarks*, especially in oral tasks, hampers the reliability and comparability of LLM-based tools (Leu Jr, 1982).

Our position. While LLMs offer scalable solutions for task prediction in English Education, their current limitations—such as misalignment with expert assessments, lack of empathy, and weak alignment between assessment and feedback—require ongoing refinement. *Future research* should focus on improving model transparency, enhancing the cultural and emotional sensitivity of LLMs, and refining task predictors to better reflect long-term learning trajectories and learner motivation. Additionally, developing standardized pedagogical benchmarks for error analysis will help ensure the consistency and reliability of LLM-generated feedback.

6 LLM-empowered Agent

In this section, we delve into the potential of LLMs as intelligent tutoring agents in English Education. LLMs can act as catalysts for personalized learning, addressing the long-standing scalability, adaptability, and inclusivity challenges in traditional teaching paradigms.

6.1 Fundamental Abilities

This section highlights five key abilities of LLM-empowered agents that enable them to function as adaptive tutors.

Knowledge Integration. LLMs excel at merging structured educational knowledge graphs (Abu-Rasheed et al., 2024; Hu and Wang, 2024) with unstructured textual data (Li et al., 2024c; Modran et al., 2024), providing rich, contextualized information on linguistic constructs and cultural nuances. Their ability to perform real-time knowledge editing (Wang et al., 2024d; Zhang et al., 2024a) ensures learners receive content aligned with evolving language usage, addressing the inherent limitations of static materials.

Pedagogical Alignment. LLMs require embedding with pedagogical principles to facilitate genuine learning experiences (Carroll, 1965; Taneja, 1995). Recent work incorporates theoretical frameworks, such as Bloom's taxonomy (Bloom et al.,

1956), to guide LLMs in systematically addressing different cognitive levels (Jiang et al., 2024b). Approaches like *Pedagogical Chain of Thought* (Jiang et al., 2024b) and *preference learning* (Sonkar et al., 2024; Rafailov et al., 2024) focus on aligning model responses with educational objectives.

Planning. By assisting in crafting teaching objectives and lesson designs, LLMs can handle complex tasks such as differentiated instruction (Hu et al., 2024). LessonPlanner (Fan et al., 2024) has been proposed to assist novice teachers in preparing lesson plans, with expert interviews confirming its effectiveness. Zheng et al. (2024) propose a three-stage process to produce customized lesson plans, using Retrieval-Augmented Generation (RAG), self-critique, and subsequent refinement.

Memory. Effective tutoring systems track learner histories and tailor subsequent interactions accordingly (Jiang et al., 2024a; Chen et al., 2024). When serving as memory-augmented agents, LLMs can retain individualized data—such as repeated grammar mistakes or overlooked vocabulary—thereby improving continuity and enabling consistent scaffolding of future learning tasks.

Tool Using. Beyond textual interactions, LLM-based agents can integrate specialized tools to streamline the educational ecosystem, from cognitive diagnosis modules (Ma and Guo, 2019) to report generators (Zhou et al., 2025). By orchestrating these resources, LLMs seamlessly unify diverse utilities under a single interface, enhancing learner experience and instructional efficiency.

6.2 Applications

Although still in its early stages, LLM-empowered agents have already started to show promising applications in English Education.

Classroom Simulation. Classroom simulation leverages LLM-empowered agents to recreate complex, interactive learning settings without the logistical hurdles of organizing physical classrooms (Zhang et al., 2024b). By simulating virtual students and tutors, researchers can study pedagogical strategies at scale, generate diverse learner interactions, and refine teaching techniques. Moreover, this virtual data can be used to fine-tune LLMs for specific educational contexts and learner profiles (Liu et al., 2024b), offering a cost-effective and adaptable approach to language instruction.

Intelligent Tutoring System (ITS). LLM-based agents have demonstrated the capacity to provide dynamic, personalized tutoring experiences (Wang et al., 2025; Kwon et al., 2024), effectively identifying learner weaknesses through large-scale linguistic analysis (Caines et al., 2023). This makes them promising for delivering individualized instruction at scale. Although current ITS applications in mathematics (Pal Chowdhury et al., 2024) and science (Stamper et al., 2024) have shown success, the extension to English Education requires nuanced handling of cultural and contextual elements, as well as the unpredictability of human language usage.

Discussion. Despite the promise of these applications, critical challenges remain. Existing classroom simulation frameworks often *lack standardized benchmarks for English Education*, making it difficult to assess the efficacy and generalizability of developed systems (Zhang et al., 2024b). In addition, evaluating language-specific tutoring strategies, including real-time conversational practice and holistic skill integration, remains an underexplored frontier. Addressing these gaps requires *new datasets and metrics* centered on holistic skill development and interdisciplinary collaboration.

Our position. We argue that *future research* should focus on integrating multimodal learning tasks (Sonlu et al., 2024) and developing standardized frameworks for evaluating English Education simulations. Moreover, LLMs should evolve beyond text-based capabilities to provide real-time, context-sensitive feedback, particularly in speaking and listening. Interdisciplinary collaboration and the creation of new datasets tailored to English Education are crucial for refining these systems and ensuring their scalability and inclusivity in language instruction.

7 Conclusion

This paper emphasizes the transformative potential of LLMs in English Education, positioning them as valuable tutors to complement traditional teaching methods. Through their roles as data enhancers, task predictors, and agents, LLMs can provide adaptive learning experiences across the core skills of listening, speaking, reading, and writing. This paper encourage continuing dialogue and interdisciplinary collaboration to responsibly integrate LLMs into educational ecosystems.

Limitations

Emphasis on potential over practical implementation barriers. This paper primarily focuses on the potential of LLMs to serve as effective tutors in English Education, outlining beneficial roles as data enhancers, task predictors, and agents. While we acknowledge the existence of challenges (to be discussed in Appendix C), a limitation of this position is that the main arguments may not fully capture the considerable practical, socio-economic, and infrastructural hurdles that could impede the equitable and effective implementation of these LLM roles across diverse global educational contexts and resource settings.

Generalizability and contextual adaptation of proposed roles. We propose three broad roles for LLMs in English Education. However, this paper does not provide an exhaustive analysis of how the efficacy and suitability of LLMs in these roles might vary significantly across different target languages (especially low-resource languages), specific learner demographics (e.g., preschoolers vs. K-12 vs. adult learners, learners with disabilities), diverse cultural contexts, or varying pedagogical philosophies. The general framework presented may require substantial adaptation and further research to be effectively applied in specific English Education scenarios.

Nuances of human-LLM pedagogical interaction. While advocating for LLMs as tutors that can complement human expertise, this position paper does not delve deeply into the complex dynamics of the pedagogical interactions between learners, LLM-based tutors, human educators, and parents. Critical aspects such as optimizing the collaborative model, designing effective training for educators to leverage LLMs, mitigating risks of learner over-reliance, and ensuring that LLM interactions foster deep learning rather than superficial engagement are multifaceted issues that warrant more extensive investigation than afforded by the scope of this paper.

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A Literature Review

We provide an overview of LLM-centric research of English Education presented in Figure 4.

B Four Phases of Research Roadmap

Stage 1: Rule-based Models (1960s–1990s). Early solutions relied on handcrafted linguistic rules to process language in tightly constrained scenarios (Grosan et al., 2011; C Angelides and Garcia, 1993). Classical platforms like PLATO (Hart, 1981) and Systran (Toma, 1977) operated effectively for highly structured tasks (e.g., grammar drills) but struggled with complex, context-dependent interactions.

Stage 2: Statistical Models (1990s–2010s). With the increased availability of digitized corpora, methods such as the early version of Google Translate (Och, 2006) and Dragon NaturallySpeaking (Blair, 1997) pioneered statistical pattern mining. These approaches leveraged large datasets to infer linguistic rules probabilistically, improving scalability yet still lacking deeper semantic understanding.

Stage 3: Neural Models (2010s–2020s). The advent of deep learning architectures (e.g., RNNs (Yu et al., 2019) and Transformers (Vaswani, 2017)) enabled more robust context modeling, sparking transformative applications like Grammarly (Fitria, 2021) and Duolingo (Vesselinov and Grego, 2012). These systems offered enhanced personalization and feedback, significantly augmenting learners' writing and reading comprehension.

Stage 4: Large Language Models (2020s–Present). Nowadays, various LLMs (e.g., ChatGPT (Achiam et al., 2023)) combine massive pretraining with instruction tuning, achieving impressive results in multi-turn dialogue, individualized scaffolding, and multimodal integration. Tools such as Khanmigo (Anand, 2023) demonstrate LLMs' potential for real-time conversational practice, dynamic content creation, and inclusive educational support at scale.

C Challenges and Future Directions

While we posit that LLMs have the potential to revolutionize English Education, realizing their full promise requires addressing key challenges. This section offers a concise overview of these challenges, followed by directions that could guide future research and deployment.

Ensuring Reliability and Mitigating Hallucinations. LLMs may produce hallucinations (Huang et al., 2023) that can mislead learners and undermine pedagogical goals. This risk intensifies in high-stakes educational environments, where trust and correctness are paramount. Future directions include enhancing data quality and diversity for training (Long et al., 2024), developing techniques to integrate LLM outputs with structured domain knowledge and pedagogical rules, and employing rigorous automated and human-in-the-loop validation mechanisms to minimize such detrimental outcomes and improve the factual grounding of LLM-generated educational content.

Addressing Bias and Ethical Considerations. As LLMs inherit biases from their training data, these systems may produce culturally insensitive, stereotypical, or unfair responses, potentially harming students from diverse linguistic and sociocultural backgrounds. Moreover, significant privacy concerns emerge when collecting and using learner data to personalize instruction, particularly for K-12 students. Future research must focus on developing robust governance frameworks, transparent documentation of data sources and model behaviors, and advanced bias detection and mitigation strategies (Borah and Mihalcea, 2024; He and Li, 2024) to ensure that LLM-based tools for English Education are equitable, fair, and uphold stringent data protection standards.

Aligning With Pedagogical Principles. LLMs excel at generating fluent language but often lack deep pedagogical alignment, particularly for tasks requiring developmental sensitivity, learner motivation strategies, or differentiated instruction tailored to individual learning needs. Their general-purpose nature means they do not inherently account for established language acquisition theories or specific curricular standards (Razafinirina et al., 2024). A crucial future direction is the development of methodologies to better imbue LLMs with pedagogical intelligence. This includes co-designing LLM applications with educators, fine-tuning models on high-quality pedagogical interaction data, and creating architectures that can dynamically adapt to learners' cognitive states and developmental needs in English language learning.

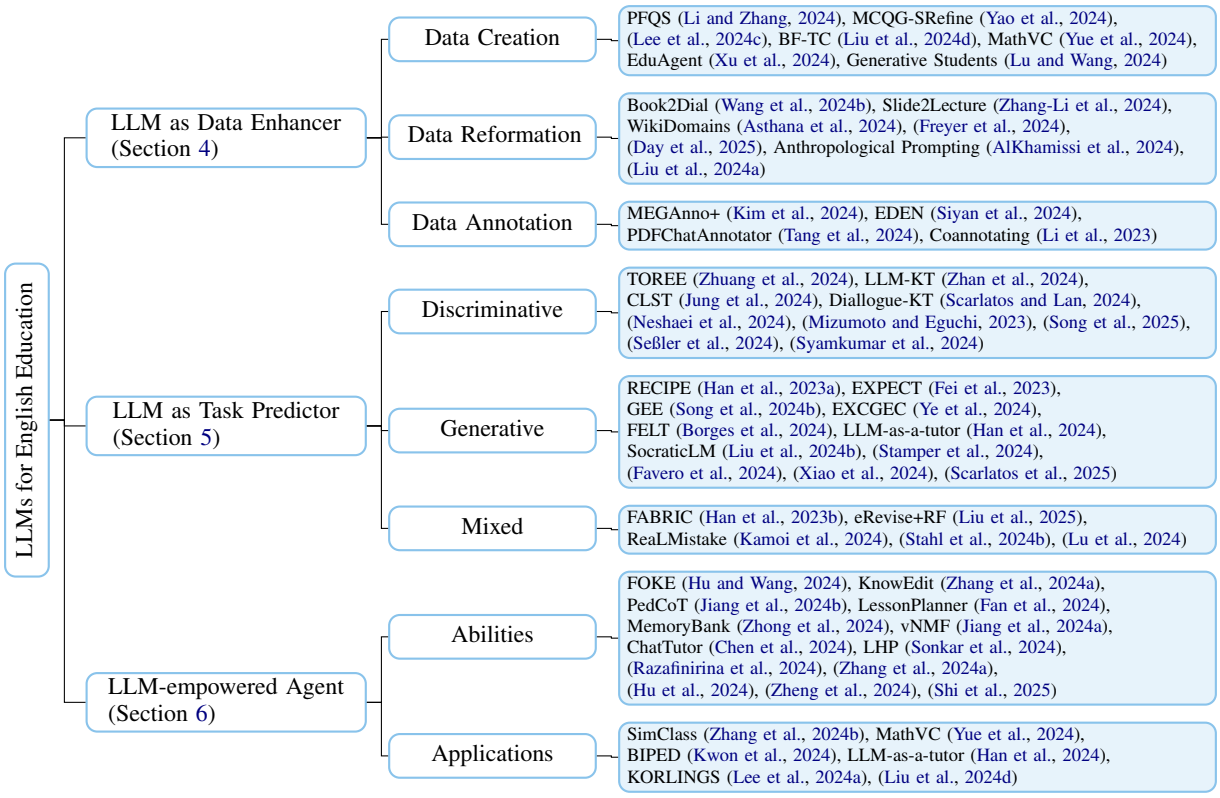

Figure 4: An overview of LLM-centric research of FLE.

Establishing Robust Evaluation Frameworks. A significant challenge in leveraging LLMs for English Education is the current lack of widely accepted and easily implementable evaluation frameworks to assess the quality of LLM-based teaching interactions and outcomes. Existing metrics often focus on linguistic correctness or task completion (Tan et al., 2024; Macina et al., 2025) rather than pedagogical efficacy or impact on learning (Chiang et al., 2024). Future work should prioritize the development of standardized evaluation methodologies, including comprehensive benchmarks and nuanced metrics that capture both the accuracy of linguistic information and the pedagogical value of LLM interventions. This will be essential for comparing different systems and guiding iterative improvements.

Integrating with Standardized Educational Frameworks. English language learning is often governed by established standards and frameworks, such as the Common European Framework of Reference for Languages (CEFR) or Common Core State Standards (CCSS). For LLM-based tools to be truly effective and gain acceptance, their outputs and interaction patterns should align with these existing frameworks. Future technical development should focus on enabling LLMs to reference, interpret, and operate consistently within these standards (Nicholls et al., 2024; Imperial et al., 2024). This includes generating proficiency-level-appropriate content, providing feedback that corresponds to specific framework descriptors, and assisting learners in achieving standardized learning objectives, thereby enhancing usability, conformity, and trustworthiness among educators and learners.

Fostering Human-AI Collaboration in Pedagogy. While LLMs offer transformative potential, it is unlikely they will completely replace human teachers in English Education in the foreseeable future. Instead, the most promising path involves developing sophisticated human-AI collaborative educational technologies (KIM et al., 2025). Future research should explore how LLMs can best function as assistive tools that augment, rather than supplant, the capabilities of human educators (Shojaei et al., 2025). This includes designing intuitive interfaces for teachers to guide, customize, and oversee LLM-driven activities, investigating teachers' perspectives on integrating LLMs into their practice, and defining technical benchmarks for when an LLM possesses sufficient acquired skills to reliably as-

sist teachers. The focus must be on a synergistic model where LLMs handle scalable tasks while human teachers provide the crucial elements of empathy, nuanced understanding, and holistic student development.

D Alternative Views

While this paper supports using LLMs in English Education, it is essential to consider alternative perspectives. Below, we discuss two key opposing views and provide counterarguments.

D.1 Task-Specific or Language-Specific Models as Better Alternatives

Some argue that specialized or language-specific models, including classical ML systems with carefully engineered features, can outperform general-purpose LLMs in narrowly defined tasks (e.g., phonetics or grammar drills (Fang et al., 2023)). By focusing on limited objectives, such models avoid the computational overhead and potential inaccuracies of LLMs, which aim to handle a broader range of inputs and contexts (Shen et al., 2024a).

Counterargument. While specialized models may excel in isolated tasks, they lack the flexibility required for comprehensive English Education, which involves cultural nuances, conversations, and evolving learner needs. In contrast, LLMs can be fine-tuned for specific goals while still offering broader linguistic competence (Song et al., 2024a). Additionally, relying on multiple specialized models can be resource-intensive, whereas a well-configured LLM provides a unified framework that balances specialization and scalability.

D.2 Concerns About Over-Reliance on LLMs

Critics warn that over-reliance on LLMs may lead to problems such as generating misleading outputs (Nahar et al., 2024), reducing human interaction, and over-standardizing teaching methods. These issues could undermine the interpersonal and motivational aspects of language learning.

Counterargument. These risks highlight the need for balanced integration rather than the replacement of human tutors. LLMs can complement educators by automating repetitive tasks, allowing teachers to focus on individualized support and motivation. Advances in AI safety, such as feedback loops (Tong et al., 2024) and human-in-the-loop systems (Wu et al., 2022), can help minimize inaccuracies (Ho et al., 2024). Additionally, the fine-tuning capabilities of LLMs ensure adaptability, supporting diverse and inclusive learning experiences (Lee et al., 2024b).