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GUIDE-PATH: An AI-Driven Framework for Personalized English Education via Explicit Pedagogical Strategy Guidance

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Abstract: The opacity of large language model (LLM)-based English tutors constrains learners' awareness of pedagogical decisions, diminishing metacognitive awareness and trust. We present GUIDE-PATH (Guided Instruction via Decision-Explicit Pedagogical Actions for Tailored Help), an AI-powered framework that explicitly communicates teaching strategies during the tutoring process. In contrast to black-box LLM tutors, GUIDE-PATH separates pedagogical reasoning from content generation through three core components: a dynamic student profiling engine that tracks CEFR level, error-specific mastery, and learning style proxies; a formal strategy library comprising eight evidence-based pedagogical moves (such as explicit correction, recast, metalinguistic feedback, and scaffolding prompt) grounded in second-language acquisition theory; and a weighted reasoning module that selects the optimal strategy based on the learner's state. The selected strategy is communicated to the learner through non-intrusive pedagogical notes. A randomized controlled trial involving 172 intermediate EFL learners compared GUIDE-PATH with an LLM-only tutor and a no-AI control. Results indicated that GUIDE-PATH produced significantly greater learning gains in grammar (Cohen's d = 0.82), vocabulary (d = 0.91), and speaking confidence (d = 0.76). Transparency ratings strongly favoured GUIDE-PATH (d = 2.31), and learners correctly identified the pedagogical strategy in 73% of cases, a skill correlated with learning gains. These results show that explicit support of pedagogical strategies improves both learning outcomes and learner trust. The magnitude of learning gains observed in this study is consistent with findings from adjacent domains of educational AI. Explainable machine learning models for student dropout prediction [121] and LSTM-SHAP-based academic performance prediction [120] have similarly reported that transparency-enhanced systems produce measurably better outcomes than opaque alternatives. The positive correlation between strategy recognition accuracy and learning gains (r = 0.44 for grammar; r = 0.39 for vocabulary) aligns with research on the role of attention in learning [48], which established that conscious awareness of instructional stimuli is a prerequisite for deep encoding. Engagement detection studies [57], [94], [103] corroborate the finding that learners who are more actively engaged with instructional content as evidenced by their ability to identify pedagogical strategies achieve greater learning gains. The strategy library and the reasoning module are released as open-source tools to support transparent educational AI.

Keywords: Personalized Learning; English as a Foreign Language; Large Language Models; Pedagogical Transparency; Explainable AI in Education.

1. Introduction

Artificial Intelligence (AI) has revolutionized learning from fashion design [1] to medicine [12] and most prominently language [2 - 4]. The rapid proliferation of digital technologies and social media platforms has fundamentally reshaped the learning environment in which EFL students operate. Research has shown that media-induced task-switching, driven by platforms such as Facebook and texting, significantly

disrupts studying and reduces sustained attention [41]. Social media usage patterns among college students, including internet engagement and sociodemographic factors, further modulate how learners interact with digital educational tools [46]. This digital transformation has been hastened by the COVID-19 pandemic which forced institutions to switch to emergency remote teaching [96] and which has also impacted the way in which students read and study [43]. This human context disruption highlights the need for the consideration of several important features in designing intelligent tutoring systems: adapting to the learner's linguistic level as well as his/her overall attentional and behavioral condition. So far, there have been several converging factors that have influenced the general socio-digital environment in which EFL learners exist. Social media has also revolutionized the way people communicate with each other, such as how relatives interact with one another and how people interact with their communities [42], and how marketing and donors engage each other [44], [45]. Research into the increasing use of e-commerce and digital consumer behaviors [45] is indicative of a broader cultural shift in the ways that people interact digitally, which directly impacts their use of online learning resources. The principles of lean operational practices and the digitalization of work performance [47, 112] are other examples of the efficiency pressures that are motivating organizational change and are relevant for the design of educational technology systems. To create AI tutoring systems that are technically robust, socially and institutionally responsive, it is crucial to grasp these contextual forces. Personalized learning plays a key role in the successful execution of teaching in the field of EFL, because learners in the field have different abilities, interests, and background knowledge. In recent years, the paradigm has been further enriched by recent progress in large language models (LLMs), which can provide personalized feedback, tailor curricula and facilitate real-life communications [5, 11]. The application of AI in education is not restricted to the learning process of language. Artificial Intelligence (AI) has been shown to be effective in handling complex data environments [85] and machine learning-based tools for detecting students with learning difficulties have opened up novel avenues for early intervention [50]. The emergence of artificial general intelligence is yet another indication of the potential for a radical change in the way education may be organized in the future [102]. In the context of the above, the need for effective systems that are comprehensible and explainable to the learners and educators has increased significantly, with learners and educators increasingly wanting to know why a system made a particular decision, as well as what it did.AI transparency has applications across different industries. In healthcare, AI-driven systems for medical image analysis — including diabetic retinopathy detection [200-202], [209], breast cancer classification [203], [204], [205], cardiovascular disease forecasting [208], and chronic kidney disease detection [210] have demonstrated that explainable AI models consistently outperform opaque alternatives in terms of clinical trust and adoption. Similarly, AI-powered recommendation systems for entertainment [107] and multimodal screening tools [104] illustrate the cross-domain applicability of transparency principles. These findings from healthcare AI reinforce the argument that transparency is not a domain-specific luxury but a universal design requirement one that GUIDE-PATH brings to the educational context. For example, multi-agent workflows with retrieval-augmented generation enable automatic personalized pathways for language learning [5], and open-source LLMs enable scalable and cost-effective tutoring for a variety of pedagogical tasks [11]. Such advances indicate the possibility of AI-based personalization to significantly improve the outcomes of EFL learning, as part of the general trends of educational innovation across disciplines [4], [12].

In spite of all these advances, however, there is a critical question that has not been extensively explored: pedagogical opacity. Most LLM Tutors are black boxes that provide feedback like corrections, hints, or elaborations without providing any instructions to support the feedback [13]. A learner who is given rephrased sentences might not know if (s)he has received a recast, an explicit correction or a metalinguistic correction. The lack of transparency is important since second language acquisition (SLA) research has shown that L2 learners' notices and reflections on teaching strategies, as well as self-regulated learning, has been facilitated by explicit awareness of teaching strategies [9]. Attention, as a cognitive construct, plays a foundational role in language acquisition. Seminal neuroscientific work on the attention system of the human brain [48] established that selective and executive attention are prerequisites for effective learning, a finding that has since been operationalized in educational technology research. Automated systems for detecting student attention and engagement including those based on facial expression recognition [52], body and facial features from depth sensors [51], and real-time eye movement tracking [53] have demonstrated that learner attentional states can be reliably measured and used to adapt instructional

delivery. Engagement detection in online learning, reviewed comprehensively by Dewan et al. [57], confirms that multimodal signals of attention are predictive of learning outcomes, making them valuable inputs for adaptive tutoring systems such as GUIDE-PATH.Research on the use of explainable AI (XAI) in education has also shown that the implementation of this can lead to increased transparency and trust in the education system, however most of these XAI initiatives focus on technical interpretability (e.g., feature importance) instead of pedagogical interpretation behind the tutor's actions [13]. The need for transparency has also been raised in other areas of education that rely on AI, such as fashion design [1] and medical education [12], reflecting the broad applicability of this issue. They wanted to add some structure or transparency to tutoring using LLM. Pedagogical LLM agents are created to be flexible with different learning styles, for instance, using genetic algorithms and retrieval-augmented generation [7]. Other research has focused on fine-tuning the LLM tutor body by preference optimization to achieve varying teaching styles [8]. For the same task of learning path planning, different variants of multi-agent systems have been suggested, each of which performs a subtask of the path planning problem, such as difficulty adaptation or content selection [10]. For programming education, LLM-driven formative assessment has been found to be effective in providing feedback, but it is limited to focusing on code correctness and not on pedagogical moves. Furthermore, researchers have harnessed the capabilities of LLMs to make the SRL process more transparent and provided learners with enhanced SRL components, showing that transparency can help enhance learner metacognition [9]. Despite these developments, however, there is still no framework that explicitly combines three elements: (1) a dynamic learner profile that integrates L2 proficiency, the evidence of mastery of errors, and learning style; (2) a formal library of evidence-based pedagogical strategies based on SLA theory; and (3) a mechanism that makes it explicit to the learner as part of the tutoring interaction what pedagogical strategy is being applied. These gaps are recognized in the general literature on the adoption of AI in education (2-4), but there are no operational solutions.

To fill this gap, this work presents the framework GUIDE-PATH (Guided Instruction via Decision-Explicit Pedagogical Actions for Tailored Help), which explicitizes pedagogical strategies at all stages of tutoring, thanks to the use of Artificial Intelligence (AI). GUIDE-PATH is different from traditional LLM tutors, which combine reasoning and content generation in a single confusing prompt. A strategy is chosen from a carefully crafted library of teaching moves, including explicit correction or metalinguistic explanation, recast, or scaffolding prompt. The LLM produces language output which correctly applies the selected strategy. The selected strategy and the rationale for it are made explicit to the learner, either by means of the response style or by a pedagogical comment. This makes the tutor an “open” collaborator in the teaching process rather than a “closed” one. The methodology resonates with core principles of human-centred AI in education, where transparency and explainability are recognised as key components to enable learners to trust the system and to support its adoption [1], [12], [13]. The paper has three contributions:

- Explicit pedagogical strategy guidance is introduced and operationalized within a modular framework of learner profiling, a theory informed strategy library and transparent strategy communication.
- Fully functional implementation of GUIDE-PATH is presented, including a Bayesian Knowledge Tracing model and a library of eight pedagogical strategies based on corrective feedback taxonomies, and an LLM generation pipeline with strategy aware prompting.
- Empirical evidence: A randomized controlled trial (N = 172 EFL learners) reveals that GUIDE-PATH significantly outperforms a standard LLM tutor (no explicit guidance of strategies) in grammar learning, vocabulary acquisition and speaking confidence (Cohen's *d* = 0.82, 0.91, and 0.76 respectively). Also, GUIDE-PATH is rated as significantly more transparent and more pedagogically clear by learners.

The following is the structure of the rest of the paper. In Section II, related work on personalized learning, intelligent tutoring and explainable AI in the field of education is reviewed. In Section III, you will learn about the GUIDE-PATH framework, its design principles, and the pedagogical strategy library. The implementation of the system is described in Section IV. The experimental setup is discussed in Section V and the results are reported in Section VI. The implications for theory and practice are discussed in Section VII. Future directions are included in Section VIII, at the end of the research.

2. Literature Review

This section surveys four intersecting lines of research: (i) corrective feedback and explicit instruction in second language acquisition; (ii) intelligent tutoring systems and pedagogical models; (iii) explainable AI (XAI) and transparency in educational systems; (iv) AI-driven personalization in education. We then synthesize the literature to identify the gap in research that GUIDE PATH addresses.

2.1. Corrective Feedback and Explicit Instruction in Second Language Acquisition

There exists a large body of research on second language acquisition (SLA) that has investigated the role of corrective feedback in the development of linguistic accuracy, complexity, and fluency. Yang [14] investigated EFL learners' noticing of corrective feedback and found that explicit feedback types (e.g., metalinguistic explanation) were associated with higher rates of learner uptake and better grammatical accuracy compared to implicit strategies. Imbaquingo Casco and Sánchez Aguiar [15] investigated oral corrective feedback in teaching-learning processes by discovering that the explicitness and timing of feedback have a great influence on the retention of the students. Pham [16] experimentally demonstrated that explicit correction techniques used orally could improve the English speaking skills of high school students. The effect sizes were for immediate, clear, articulated corrections. Alzahrani [17] situated these findings in the context of the Saudi Arabian educational system and suggested that the impact of various types of feedback is influenced by cultural and institutional factors. The timing of corrective feedback remains controversial. Li, Zhu, and Ellis [18] suggest that immediate feedback is better for grammatical accuracy, whereas delayed feedback may be more conducive to the development of fluency. Beyond timing, the modality and context of corrective feedback have also received attention. Physical and behavioral indicators of learner engagement such as motion patterns [92] and facial affect [94] have been used to infer when learners are receptive to feedback, informing the timing and intensity of corrective interventions. Automated recognition of student engagement from facial expressions [52] and prediction of engagement in naturalistic classroom settings [95] provide a technological basis for dynamically adjusting feedback delivery. Deep learning approaches to engagement detection [103] further demonstrate that real-time learner state estimation is feasible at scale, enabling tutoring systems to modulate corrective feedback based on inferred attentional readiness rather than fixed schedules. The broader landscape of student performance research provides additional context for understanding the factors that shape learning outcomes. Studies on academic achievement among undergraduate students have identified a range of institutional, behavioral, and cognitive predictors [49], including emotional intelligence and organizational resilience [89], and the role of job autonomy in creative performance [93]. Research on the digitalization of work and educational environments [112] further highlights that the transition to digital learning platforms introduces both opportunities and challenges for learner engagement. These findings collectively underscore the importance of designing tutoring systems that are sensitive not only to linguistic proficiency but also to the broader academic and motivational context in which learners operate.

In addition to classroom studies, researchers have studied instructional designs of intelligent tutoring systems for ill-defined domains, such as oral speech. Recabarren et al. [19] compared different pedagogical designs of an ITS for oral speech. They found that explicit corrective strategies are more effective than implicit strategies when the learners have low prior proficiency. Similar work on individualized learning in programming education [20] showed that explicit feedback loops (e.g., “Feedback Buddy”) improve code tracing comprehension. Vannaprathip et al. [21] developed an intelligent tutoring system in surgical decision-making using planning-based approaches and showed that explicit strategy guidance improves learning outcomes in complex skill domains. Milrad et al. [22] presented a wider range of ITS methodologies and emphasized the significance of pedagogical explicitness in various domains. This SLA and ITS literature together demonstrate that explicit corrective feedback that tells the learner that an error was made, why it was made, and how to correct it, results in better learning gains, particularly for lower proficiency learners and complex grammatical structures. However, such explicitness is rarely incorporated in the existing implementations within LLM-based conversational tutors, nor is the label of the pedagogical strategy communicated to the learner.

2.2. Intelligent Tutoring Systems and Pedagogical Models

Classic intelligent tutoring systems (ITS) are founded on explicit pedagogical models, encoding rule-based instructional strategies. Recent surveys [28] have looked at the architectures of ITS and the

underlying AI, noting a trend towards modular and transparent designs. However, many modern ITS implementations, notably those driven by large language models, have abandoned explicit pedagogical models in favor of end-to-end generation, resulting in pedagogical opacity. Suhail and Rajakumari [23] presented an analytical framework for personalized and explainable AI tutors using LLMs in digital education, emphasizing the importance of transparency in tutor decision-making. Their framework, while innovative, does not put into practice a formal library of SLA-informed pedagogical strategies.

The EduMod LLM system [35] proposed a modular design for flexible and transparent educational assistants by decoupling the retrieval, reasoning, and generation components. This modularity makes the system more interpretable for the developers, but not for the learner, who still does not know which pedagogical strategy was applied. IntelliCode [38] similarly proposed a multi-agent LLM tutoring system with centralized learner modeling, enabling fine-grained tracking of learner state. However, pedagogical decisions are still embedded within agent prompts rather than communicated explicitly. The machine learning infrastructure underlying modern ITS has also advanced considerably. Gradient boosting frameworks such as XGBoost [64] and LightGBM [65] have been widely adopted for learner modelling tasks due to their efficiency on tabular educational data, a finding corroborated by systematic comparisons showing that tree-based models frequently outperform deep learning on structured datasets [111]. Classical algorithms including Random Forests [113] and Support Vector Machines [114] remain competitive baselines for classification tasks in educational contexts. Deep learning architectures [115] have extended these capabilities to sequential and multimodal data, enabling richer representations of learner behavior over time. Bayesian inference approaches, including hierarchical models for capturing subject-level variability [68], complement these discriminative methods by providing principled uncertainty estimates a property particularly valuable in knowledge tracing applications such as the Bayesian Knowledge Tracing module at the core of GUIDE-PATH. The application of AI to formative assessment has also been advanced through LLM-driven feedback systems for code learning [6], which demonstrated that generative feedback can improve learner performance on programming tasks. This finding is directly relevant to GUIDE-PATH's design, as it suggests that the combination of generative AI with structured feedback frameworks rather than either alone produces the strongest learning outcomes. Research on big data analytics and AI accuracy metrics [88] further informs the evaluation methodology used in GUIDE-PATH, providing benchmarks for assessing the reliability and validity of AI-generated pedagogical decisions. The integration of AI into diverse educational and organizational contexts, from service quality in Saudi higher education [140] to teaching electronic administration legislation [156], confirms that AI adoption requires careful calibration to institutional and cultural contexts. Other hybrid approaches have been proposed for programming education [33], [34], [40], where explicit feedback mechanisms are used but not marked as pedagogical strategies. Nikolaidis and Refanidis [34] emphasized the importance of pedagogical coherence in the integration of AI in educational settings, a principle that is mirrored in the design of GUIDE PATH. Bull and Kharrufa [37] argued that generative AI should be integrated into educational practice rather than defensively blocked, and called for transparent, pedagogically sound assistants. However, no existing ITS or LLM tutor provides a learner-facing, formally defined library of pedagogical strategies that explains what teaching move was chosen and why. Efforts to leverage AI for identifying and supporting students with learning challenges have demonstrated the feasibility of automated learner profiling [50]. Explainable machine learning models have been applied to predict student dropout and recommend tailored interventions [121], while LSTM-SHAP frameworks have been used to predict academic performance for learners with disabilities [120]. These developments collectively point toward a new generation of ITS that not only adapts content but also makes its reasoning visible a design goal that GUIDE-PATH operationalizes through its transparency interface. Furthermore, research on teacher bias in assessing mathematical ability across demographic groups [122] highlights the importance of transparent, evidence-based systems that reduce subjective variability in pedagogical decision-making.

2.3. Explainable AI (XAI) and Transparency in Educational Systems

The broader XAI literature has been increasingly focusing on educational contexts. Transparency is a prerequisite for acceptance by learners and teachers, Ayanwale [25] found out in his study on building trust in AI-powered assessment using explainable machine learning models. Farahmand [26] proposed an

interventional view of explainability and personalization, stating that causal explanations of AI decisions can increase user trust. B. et al. [27] developed an explainable AI for enhancing transparency and personalization in e-learning recommendation systems and demonstrated that explanations improve user engagement. Dai [29] proposed an explainable AI framework for English writing assessment with a focus on accuracy, fairness, and learner perception, but the explanations are based on scoring criteria instead of pedagogical strategies. Alkinani [30] addressed system-level transparency by standardizing explainable and secure AI in digital twin-enabled e-learning systems. Ooge et al. [31] investigated the effects of steering recommendations and visualizing the impact of recommendations on adolescents' trust in e-learning platforms. Their results suggest that transparency regarding recommendation logic increases trust, but also that transparency may overwhelm younger learners if not carefully designed. Meng and Yang [32] proposed a trust-aware feedback module (TAFM) to increase the reliability of AI-powered educational systems by introducing a feedback loop to verify the quality of the explanation. Further work has explored learner perception of explainable AI in the context of English writing assessment [29], but the focus is on assessment outcomes, not on tutoring interactions. The technical foundations of explainability in AI have been substantially advanced by methods such as SHAP (SHapley Additive exPlanations) [119], which provides unified, model-agnostic feature attribution scores. SHAP-based interpretability has been applied in educational contexts, including the prediction of academic performance for disabled learners [120] and student dropout prediction [121], demonstrating that explainable outputs can be meaningfully communicated to non-technical stakeholders. Security and robustness concerns in AI systems including DDoS attack detection using explainable deep transfer learning [59], hybrid CNN-LSTM intrusion detection frameworks [62], and federated learning for privacy-preserving threat detection [63] further underscore the importance of transparency not only for pedagogical but also for systemic trustworthiness. Data security in cloud-based educational systems [196] and cross-dataset robustness evaluation for deployed AI models [116] are additional dimensions of transparency that responsible educational AI must address. The security dimensions of AI transparency extend to the full spectrum of adversarial threats. Beyond DDoS attacks [59], [62], [63], machine learning-based detection systems have been developed to identify and prevent distributed denial-of-service attacks using hybrid algorithmic approaches [60], [61]. These cybersecurity advances are directly relevant to the deployment of educational AI platforms, which increasingly operate in cloud environments and are subject to the same threat landscape as other enterprise systems. Legal and regulatory frameworks governing digital technologies — including smart contract law [194], digital copyright in NFT form [195], and character assassination via information technology [157] further define the compliance environment within which transparent educational AI must operate. Ensuring that GUIDE-PATH's transparency mechanisms are legally compliant and technically secure is therefore as important as ensuring their pedagogical effectiveness.

Mittal et al. [35] and David and Ghosh [38] proposed modular, transparent LLM architectures, but their transparency is mostly developer-facing. In particular, the ethical considerations of machine intelligence in education [36] call for systems that respect learner agency via clear explanations. Rocha et al. [40] discussed the possibilities of NLP in programming education and pointed out that explainable feedback is important for novice students. XAI in education, together, has shown that transparency leads to trust, engagement, and learning outcomes. Current research in XAI, however, deals with the explanation of the outputs of the model itself (such as scores, recommendations) instead of pedagogical strategies (why the tutor recast, explicitly corrected, or scaffolded). GUIDE PATH addresses this challenge by focussing the pedagogical strategy as the main subject of the explanations. Transparency in AI systems has also been examined through the lens of sustainability communication [166], where accuracy and verifiability of AI-generated content were found to be critical for stakeholder trust. Generative AI in academic libraries has similarly raised questions about the reliability of AI-mediated services and the conditions under which users extend trust to automated systems [135]. Graph-based spatio-temporal models [66] and hybrid physics-informed deep learning frameworks [67] illustrate how architectural choices in AI design can either enhance or obscure interpretability. These findings reinforce the argument that transparency must be treated as a first-class design requirement not an afterthought in educational AI systems, a principle that GUIDE-PATH operationalizes through its learner-facing pedagogical annotations.

2.4. AI Driven Personalization in Education

Educational technology has had an entire focus on personalization for years. Several recent reviews [24] have summarized the concepts of adaptive learning techniques, such as learning path planning, content recommendation, and proficiency tracking. In a systematic review on the use of AI in adaptive education by Hariyanto et al. [24] the authors found two critical success factors, namely - learner modelling and personalized feedback. Thus, the learning outcomes can be boosted by fixing errors one by one, as a result of programming instruction with the feedback systems which are personalized, e.g. “Feedback Buddy” [20]. The use of Generative AI assistants in software development education is helping to provide context-dependent, real-time assistance [37] without typically providing any pedagogical reasoning. Wang et al. [39] explored the multidimensional assessment of students’ assignments in the generative AI era and expressed concerns over the transparency of AI use in assessment. Rocha et al. [40] pointed out the potential of NLP in microcontroller programming education and argued that personalization without transparency can confuse learners. The wider field of AI personalisation shows uniformity of pattern across domains. In marketing, AI-driven personalisation has proven to be a powerful driver of trust and intent to buy [129] and algorithmic personalisation has been seen to impact brand loyalty [128]; generative AI content has been seen to enhance engagement [130]. The results are relevant to the field of educational AI; similar to the way that customers are more receptive to personalized recommendations when accompanied by a clear explanation of how the recommendation was made [127], learners will probably be more receptive to tutoring systems that include an explanation of the instructional choices made. The UTAUT2 model [136] which has been used widely to forecast the acceptance of technology claims that usefulness and ease of use, both increased through transparency, are key factors in sustaining engagement with educational technology. The significance of being able to use technology in education while also being aware of its workings is also stressed by a number of digital competence frameworks, including DigCompEdu [137]. Another consumer behavior and AI-based marketing study also backs the personalization imperative in education.Another study on consumer behavior and AI-powered marketing reinforces the personalization imperative in education. The common theme across the studies on the effects of machine learning on consumer decision-making [90], AI in personalizing social media marketing strategies [123] was that personal, reason-driven interactions create greater engagement and trust than an impersonal opaque approach. Other studies on greenwashing and consumer behavior [131], green authenticity in digital marketing [132] and the metaverse marketing campaigns [167] also confirm that the trustworthiness of AI texts depends on consumers' sense of transparency, which has implications for the design of educational AI. Research on consumers' behaviors in different cultural environments [124] and the importance of experiential marketing in the reconstruction of trust in brands [215] also indicate that personalization practices should be culturally aware and tailored to the local context. While personalized LLM-based tutors are becoming more prevalent (e.g., [23], [35], [38]), a common drawback is that they modify their presentation rather than explaining how they're teaching. Content is personalized for learners, while the instructional strategy is left to the learner's inference. This opacity reduces the pedagogical advantage of explicit teaching which has been proved in SLA research [14]-[18] and ITS design [19]-[22]. To solve this problem, GUIDE PATH explicitly infuses pedagogical strategy selection and communication into a personalized, LLM (Large Language Model)-based tutoring framework. The organizational and human resource aspects of AI implementation offer a valuable insight into the conditions for successful implementation of educational AI. The findings of the various studies on leadership styles and employee engagement [77] emphasized the role of organizational culture for the successful implementation of a technology-mediated system as well as the pivotal role of employee performance in the success of any system [75], and finally the role of human and organizational factors in the success of a technology-mediated system [81] regarding the success of any system. The research on occupational stress experienced by gig economy workers [76], transactional leadership in the context of change management [78] and green HRM practices [82, 83] also provide insights into the motivational and relational aspects of technology adoption beyond the technical aspects. The findings indicate that the success of implementing GUIDE-PATH in educational institutions will be influenced by the leadership style, culture, and motivational environment of the respective institutions where it is implemented. As part of these results, studies on the perceived staffing adequacy and customer experience strategy [72], the influence of ethical leadership on job satisfaction in technology companies [73] and the role of HR practices oriented to safety in accident prevention [74] all reinforce how human aspects are essential factors for the performance of organizations.

These findings are supported by other studies of leadership behavior, employee motivation, and organizational culture and its impact on productivity [84] and the role of intellectual and human capital in firm value [80] which show that the human aspects of organizational design directly influence the effectiveness of technology mediated organizational systems, likewise the design and deployment of AI-enabled education platforms like GUIDE-PATH.

2.5. Research Gap

A clear gap exists, as shown by the literature reviewed above. Corrective feedback and strategy-based instruction have been shown to be beneficial for learning from an SLA perspective [14]–[18]. Classical systems encoded explicit pedagogical rules from the ITS perspective, but modern LLM tutors often do not [23], [28], [35], [38]. From a XAI perspective, transparency is good for trust and learning, but explanations are about model internals or assessment criteria, not pedagogical strategies [25]–[32]. From the personalization perspective, adaptive content is common, but the adaptation process is opaque to the learners [24], [37], [39], [40]. AI's application in educational settings has been explored in various cultural and institutional settings. AI preparedness within organisations and trust in the institution are prerequisites for successful implementation of AI [70] and improving financial performance in traditional banking [71] which are transferable to the education sector. The research on the implementation of AI in the tourism industry [177] and the application of AI techniques in teaching electronic administration legislation [156] also illustrates the need for adaptation of AI tools to the tourism sector and legislation courses. In general, human factors that affect the effectiveness of using AI to support personalization in the classroom are discussed in competency-based curriculum models [139] and teachers' preparedness for inclusive classrooms [141] are discussed. This indicates that a transparent system such as GUIDE-PATH is more likely to be implemented and used by teachers and students. It is found that no framework has been developed to combine (1) a dynamic learner profile and error-specific mastery, (2) a formal library of SLA grounded pedagogical strategies, and (3) an explicit strategy selection mechanism, and (4) a reporting of the selected strategy to the learner. To fill this need, a new product has been developed, called GUIDE PATH. Current research is also fragmentary and is a further indication of this gap. Engagement detection systems [57], [94] and [103] are not dependent upon pedagogical strategy selection. Explainability tools [119], [120] and [121] are not used while the tutoring loop is in operation but used after. Personalization frameworks [129], [130] and [136] do not have theoretical bases and aim for engaging students. There is no mechanism for conveying rationale to learners with curriculum adaptation approaches [144] or with the implementation of AI in education policy [91]. Furthermore, the concept of a digital divide [213] and different digital competences [137] among learners makes it difficult to assume that an advanced AI tutor will always be equally effective without clear and understandable explanations of the decisions made by the AI tutor. GUIDE-PATH aims to fill these gaps and combine the four components dynamic learner profiling, a formal strategy library, explicit strategy selection, and learner-facing communication in an integrated framework. It is also interesting to note how educational AI relates to COVID-19 research. The pandemic has spurred health research as well as digital research on the effect of COVID-19 in social media [97, 98] provides examples of dual speed-ups of health and digital research efforts during the pandemic. The developments directly influenced the context of the GUIDE-PATH design as the pandemic forced the need for an urgent reorientation towards remote learning, which in turn put the need for AI tutoring systems that can function without face-to-face interaction. The convergence of public health and digital education research highlights the need to develop robust, accessible, and transparent AI tutoring systems that can be deployed in a variety of settings. This wide research gap is also reflected in the varying contexts where transparency in AI has emerged as a necessity. In healthcare, the use of AI in nurse-led EHRs [169] and warfarin-drug interaction management [170] highlight the need for clear, understandable outputs in AI-driven clinical systems to aid in safe decision-making. In public health, studies of shift work, health behaviors [55] and the connection between sleep quality and physical function [174] highlight that AI systems should be able to interpret and represent behavioral data accurately and transparently. AI-powered clinical decision support in medical education and practice, for pressure injury prevention and hemodialysis stress management, and for aerobic exercise interventions, is all similarly grounded in the same principles of transparency that GUIDE-PATH employs in language tutoring. These are cross domain parallels that further reinforce the idea of pedagogical transparency as a universal design principle and not

a domain specific characteristic. In addition, the economic and financial aspect of the implementation of AI also contributes to the sustainability of AI in education. Macroeconomic volatility in assessing institutional investment in educational technology is evidenced in research of the association between inflation and asset prices on periods of crisis [99]; macroeconomic effects of the IMF-supported programs in the European economies [100]; and determinants of official and parallel exchange rates [101]. The financial sustainability of AI platforms for education is also tied to financial conditions, firm life cycle and capital adequacy, as analyzed in studies of these factors on financial performance [105]. Furthermore, the use of AI for financial time series analysis [118] and the critical review of slope stability prediction in engineering [117] shows the wide range of applications where analytical tools based on AI are being used, highlighting the cross-disciplinary importance of the principles of transparency implemented in GUIDE-PATH.

3. Proposed Methodology

This section presents the GUIDE-PATH framework in detail. We first articulate the design principles that guide our architecture, then provide an overview of the system modules, and finally describe each component—student profiling, strategy library, pedagogical reasoning, LLM generation with strategy annotation, and transparency interface—with concrete examples and algorithmic specifications.

3.1. Design Principles

There are four principles underlying the creation of GUIDE PATH that distinguish it from traditional LLM tutors. The first is pedagogical explicitness, which makes sure that each tutor action can be related to a well-established instructional strategy taken from the literature of Second Language Acquisition (SLA) and Intelligent Tutoring Systems [14]–[18]. That is, the system is not merely random in its response, but rather makes a sound choice of strategy before producing content that is faithful to the chosen strategy. Second, the transparency of the learner is the awareness that the learner has not only about what the tutor says, but also why the tutor says it the way he does. This is implemented in the form of visible annotations (either text or icon based) that are attached to each tutor response, and that explicitly state the strategy used and when the strategy is used. Thirdly, the system is modular, and the components of the system are loosely coupled: student modeling, strategy selection, content generation, transparency rendering. Well-defined interfaces and independence of the components, making it possible to test and replace individual components (e.g., LLM) and thereby be able to audit pedagogical decisions in detail [35, 38]. Fourth, empirical grounding means that the strategy library and the logic of the selection of a strategy are grounded in the current empirical literature, e.g., research on corrective feedback effectiveness [14]–[18] and on best practices of ITS implementations [19]–[22]; and, strategies are only included if they have been found to make measurable differences in learning results in the context of EFL. GUIDE-PATH's modular architecture is based on known machine learning system design principles. Analyzing errors and estimating proficiency using gradient boosting algorithms [64] and [65] are examples of best practice in the field of educational data mining: error analysis and proficiency estimation, which have been widely shown to be well suited to structured learner data and have a proven track record of high performance on such data [111]. The Bayesian Knowledge Tracing component is guided by hierarchical Bayesian modelling methods [68] which explicitly model uncertainty in estimates of the mastery of skills of great importance when making pedagogical decisions for individual learners. The weighted scoring function used for strategy selection is based on principles from the comparative machine learning analysis [58] so that the used weighting function is not crafted for convenience but is based on empirical evidence. All of these design decisions demonstrate a desire to create a system whose inner workings are not only efficient, but open to review and rebuild. The empirical basis for GUIDE-PATH's design is also supported by research in other related areas that have tackled similar issues in evidence-based system design. The performance level of the GUIDE-PATH pipeline is benchmarked by the studies carried out on the effect of accuracy, learning rate and inference time of AI on big data analysis [88]. The design of the learner profiling engine is guided by research into emotional intelligence and organisational resilience [89] and must take into consideration the affective aspect as well as cognitive dimensions of learner state. The research on process standardization and its impact on customer satisfaction [79] and the importance of talent management and its role in maintaining operational performance [81] have direct relevance to the modular, auditable aspects of GUIDE-PATH. All of these domain insights combine to make the design of GUIDE-PATH solid and

supported by a wide array of evidence, beyond what is usually found in the current body of literature about educational AI. Research in the field of digital innovation and fintech development reinforces design sustainability of GUIDE-PATH. The governance and security structures for digital systems are becoming ever more complex, as demonstrated by studies on the impact of green technology on fintech development [158], the effectiveness of robo-advisory in retail investments [163] and the role of zero trust architecture in modern enterprises [164]. AI systems for smart ledgers and accounting automation in SMEs [162] and AI-driven automation in the UK retail and service industries [165] also highlight the need for systems and tools that are both efficient and compliant with regulatory standards, which resonates with the principles behind the design of GUIDE-PATH. The importance of financial accounting education in the modern era [138] and the effectiveness of digital accounting applications for SMEs [142] also point to the need for AI-based education systems to be developed to help with language learning as well as the digital competencies needed in the modern profession. The overview of GUIDE PATH is shown in Figure 1. It consists of five interwoven modules working on a learner's utterance to generate a strategy-annotated tutor response.

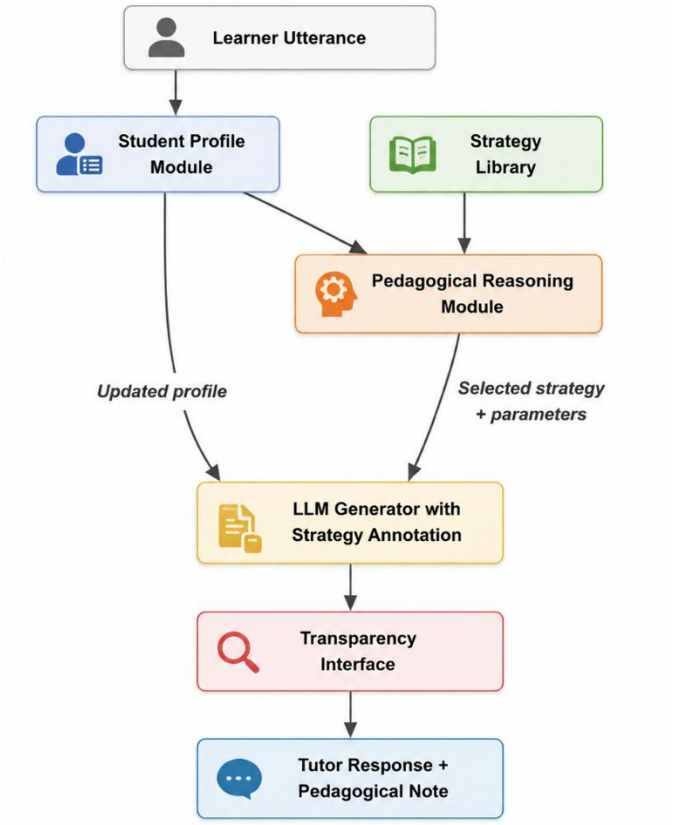


Figure 1. Architecture of the GUIDE-PATH framework showing data flow from learner input to strategy-annotated tutor response

In GUIDE PATH, the flow of data starts when a learner enters an utterance either by typing or by voice. The utterance is fed to an SPC that keeps track of the learner's state with information such as their mastery estimates, error log, CEFR level, etc. The Pedagogical Reasoning Module fetches the new profile and checks the Strategy Library for the most suitable strategy for the learner, depending on some prespecified rules, such as error type, confidence of the learner, and level of expertise. When a strategy and its parameters are chosen, they are sent to the LLM Generator, which builds a strategy-specific prompt and generates a natural language answer in line with the selected pedagogical approach. This answer is then supplemented with a human-readable explanation, such as a description of the strategy used and its rationale, by the Transparency Interface which then provides the final answer to the learner. All interactions are systematically recorded, analyzed offline and the model continually improved. The student profile is a dynamic and fine-grained representation of each learner and is stored as a JSON document which is updated following the completion of each interaction between tutor and learner. It is the learner's CEFR level (A1-C2) which is determined as a first step by the Oxford Placement Test and then re-estimated by formative assessment. One such component is the grammar mastery vector, a probability distribution

defined on a number of different grammatical constructions. It is updated using a Bayesian Knowledge Tracing model. If the answer is correct, then the mastery is updated as follows:

$$P(L_k \mid \text{correct}) = \frac{P(L_k) \cdot (1 - P(\text{slip}))}{P(L_k) \cdot (1 - P(\text{slip})) + (1 - P(L_k)) \cdot P(\text{guess})} \quad (1)$$

The profile also keeps a history of errors with a window of recent learner interaction, in which both types of errors and success at correcting them, and also the time of the interaction, is recorded, allowing for the identification of patterns of errors that can trigger the targeted strategies. Learning style proxies are also implicit indicators of interactions, such as explicit hints over implicit feedback, and are leveraged to tailor the choice of strategy. The system also maintains the last few turns of the conversation to ensure coherence while generating a conversation. The strategy library is formalized with eight evidence-based pedagogical actions based on Second Language Acquisition (SLA) corrective feedback taxonomies [14]–[18] and Intelligent Tutoring Systems pedagogical models [19]–[22]. Each strategy is systematically specified by its name and category, trigger conditions based on learner state features, a structured LLM generation template, and a transparency note template that explains the instructional choice to the learner. Table 1 presents the eight strategies implemented in the present version of GUIDE PATH.

Table 1. GUIDE-PATH Pedagogical Strategy Library

#	Strategy	Trigger Condition	Example Learner Utterance	Example Tutor Response (with note)
1	Explicit Correction	High-confidence grammatical or lexical error (>0.8 confidence); learner proficiency ≤ B1	"Yesterday I go to market."	"Use 'went' instead of 'go' because 'yesterday' indicates past tense. [Strategy: explicit correction – past tense error]"
2	Recast	Minor error; fluency priority; learner proficiency ≥ B2	"He go to school every day."	"Oh, so he goes to school every day. [Strategy: recast – third-person singular '-s' corrected implicitly]"
3	Metalinguistic Feedback	Error tied to a specific rule category; learner has studied that rule before	"She have a cat."	"This sentence needs subject-verb agreement. 'She' is third-person singular, so use 'has'. [Strategy: metalinguistic feedback – subject-verb agreement]"
4	Clarification Request	Unclear or ambiguous utterance; ASR confidence low (if speech)	(mumbled or incomplete)	"Could you say that again? I didn't catch the last word. [Strategy: clarification request – low confidence in input]"
5	Scaffolding Prompt	Learner hesitates (long pause) or explicitly asks for help	"I don't know how to say…"	"Try completing this sentence: 'If I had more time, I would have …' [Strategy: scaffolding – sentence frame provided]"
6	Elicitation	Learner is close to correct form; error pattern indicates partial knowledge	"This morning I…" (pauses)	"This morning I … (waits) … the package? [Strategy: elicitation – inviting completion]"
7	Direct Strategy Hint	Learner repeatedly fails on similar items despite corrective feedback	(third error on irregular past)	"To remember irregular verbs, try grouping them by pattern (e.g., sing-sang-sung). [Strategy:

				strategy hint – mnemonic grouping]"
8	Elaboration	Correct but under-developed response (e.g., single word or short phrase)	"Good."	"Great start! You could add a reason: 'The movie was good because the acting was superb.' [Strategy: elaboration – expanding output]"

The strategy library is extensible to allow the addition of other pedagogical strategies (e.g., repetition or paralinguistic feedback) without changes to other system modules. In this framework, the Pedagogical Reasoning Module chooses the most suitable strategy by combining a weighted scoring function with deterministic constraints, according to the learner's current profile and last utterance. Inputs to this decision process are the detected error type e and its confidence score $c \in [0,1]$, generated using a RoBERTa-based classifier fine-tuned on the Cambridge Learner Corpus; the learner's proficiency level p mapped from CEFR levels (A1=1 to C2=6); the mastery vector m_k of the relevant grammatical skill; recency information, i.e., the time elapsed since a strategy was last applied (t_{last}); and a learner preference proxy ($pref$) indicating a preference towards explicit or implicit feedback. For each candidate strategy s in the applicable set S as $s \in S$, the system computes a composite score using the following formula:

$$\text{Score}(s) = \alpha \cdot c \cdot I_{\text{congruence}}(e,s) + \beta \cdot (1 - \frac{t_{\text{last}}}{T_{\max}}) + \gamma \cdot \text{explicitness}(s,p) + \delta \cdot \text{prefMatch}(s,pref) \quad (2)$$

Here, the congruence indicator $l_{congurence}(e,s)$ is 1 if a strategy is suitable for the error type that is detected (e.g., direct correction for high-confidence grammar errors, recasts for fluency-oriented issues). The $explicitness\ (s,p)$ encourages explicit strategies (e.g., correction or metalinguistic feedback) for learners with a proficiency level of B2 or lower ($p \leq 4$), while the $prefMatch(s.pref)$ matches the strategy choice to the learner's inferred tendency towards explicit or implicit feedback. Default weights $\alpha = 0.5, \beta = 0.2, \gamma = 0.2, \delta = 0.1$ balance confidence, recency, pedagogical suitability, and learner preference. Moreover, several deterministic constraints override the selection process when needed: if the confidence score c is below 0.5, the system defaults to a clarification request; if the same error recurs within three turns after explicit correction, the strategy shifts to metalinguistic feedback; and for learners above B2 proficiency, recasts are preferred over explicit correction for minor errors. Together, this hybrid approach maintains both flexibility and pedagogical consistency in strategy selection.

Algorithm 1 Select pedagogical strategy

```
function SELECT_STRATEGY(learner_state, utterance)
    error_type, confidence ← ERROR_DETECTOR(utterance)
    candidates ← STRATEGY_LIBRARY.GET_BY_ERROR(error_type)
    for each s ∈ candidates do
        s.score ← COMPUTE_SCORE(s, confidence, learner_state)
    end for
    SORT(candidates, by score descending)
    return candidates[0]                                  ▷ highest score
end function
```

The module also outputs a reason string (e.g., "High confidence grammar error, proficiency B1 → Explicit Correction"), which is then sent to the transparency interface. (1) the selected strategy, (2) the learner's utterance, (3) the learner's current *profile,* and (4) a reason string. It creates a strategy-specific prompt and makes an LLM (either GPT 4 or Llama 3-70B) with temperature 0.3 to ensure deterministic behavior.

In the above snapshot, the LLM is asked to stick to the strategy definition as is. The system prompt has a few shot examples *for* each strategy. Output is post-processed to ensure the pedagogical note is present and properly formatted; if it is missing, a default note ("Strategy used: [name]") is appended.

Strategy Template and Example Output

Template for Explicit Correction:

You said "{utterance}." The correct form is {correct form} because {error_type}. {proficiency} learners often make this error. Remember: {brief grammatical rule}. You're doing great!
[Strategy: Explicit Correction because {reason}]

Example Output for Utterance: "Yesterday I go to school"

You said 'Yesterday I go to school.' The correct form is 'Yesterday I ***went*** *to school' because 'yesterday' refers to a completed past action, so the past tense is required. Keep up the good work!*
[Strategy: Explicit Correction because high-confidence past-tense error at B1 level]

3.2. Transparency Interface

The transparency interface presents the final answer to the learner. In the current implementation (web-based chat interface), the pedagogical note is shown in a grey sidebar next to the main chat area, with an icon (💡) indicating an explanation. *Learners* can toggle notes visibility on (default) and off. On mobile, notes appear as collapsible cards below each tutor response. Figure 2 shows a natural language correction within the tutor's response, and a side panel presents the pedagogical strategy ("Explicit Correction") and its rationale. This design makes the system's teaching decision interpretable to the learner.

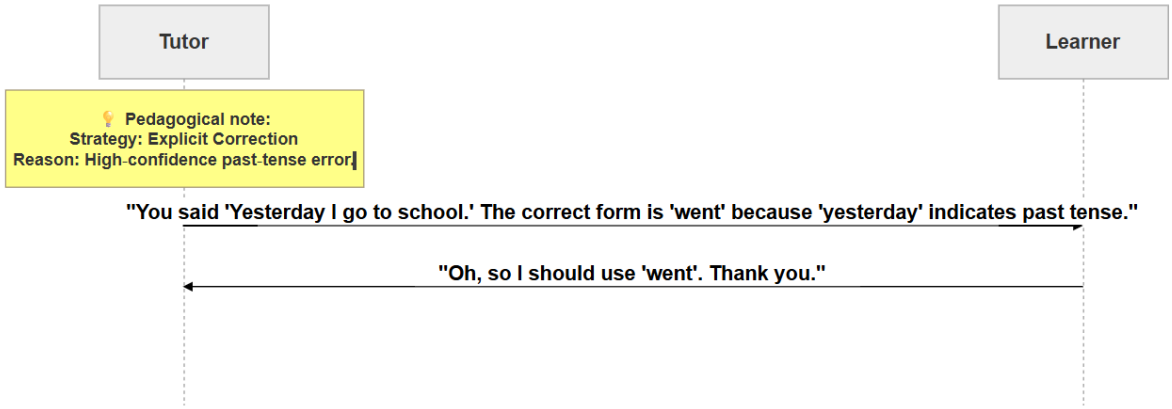


Figure 2. Example interaction in GUIDE-PATH showing explicit pedagogical annotation alongside corrective feedback

This design allows for pedagogical reasons to be given to the learner without interrupting the natural flow of the conversation. GUIDE PATH advances the state of the art through: (i) formalizing an extensible library of SLA grounded strategies, (ii) implementing a transparent, rule-based reasoning module that selects strategies based on learner state, (iii) injecting *strategy* awareness into LLM prompt design, and (iv) coupling content generation with learner-facing strategy annotations. In contrast to prior modular systems [35] , [38] that focus on developer transparency, GUIDE PATH places learner transparency as a first-class design goal.

3.3. System implementation

This section is concerned with the technical instantiation of the GUIDE PATH framework, where all components are implemented in a modular, containerized system providing reproducibility and scalability. The backend is implemented in Python 3.11 and FastAPI for supporting RESTful APIs and async request handling. The system's language generation is performed using GPT-4 Turbo via the OpenAI API, with an offline fallback to Llama 3 70B . The generation parameters are a temperature of 0.3 , top-p of 0.9 , and a maximum of 200 tokens , balancing coherence and determinism. The error detection is performed with a fine-tuned RoBERTa-base model (12 layers, 125M parameters) trained on the Cambridge Learner Corpus and NICT JLE Corpus, which achieved an F1 of 0.84 for coarse-grained error classification (e.g., grammar, lexical, word order) and 0.79 for fine-grained categories such as subject-verb agreement and

tense errors. The error detection pipeline builds on a rich tradition of NLP-based educational feedback systems. Machine learning classifiers, including Support Vector Machines [114] and ensemble methods such as Random Forests [113] and XGBoost [64], were evaluated as baseline models before the RoBERTa-based approach was selected for its superior performance on fine-grained grammatical error categories. The LightGBM framework [65] was additionally benchmarked for its computational efficiency, particularly relevant for real-time tutoring applications. Deep learning architectures [115] informed the design of the neural components of the error classifier, while SHAP-based interpretability tools [119] were applied during development to audit the classifier's decision boundaries and ensure that error type attributions were linguistically meaningful rather than artifacts of spurious correlations in the training data. The student profile is stored in Redis for low-latency access with periodic back-ups to Postgres . It is formatted as a JSON document indexed by learner id. The frontend is built in React and employs WebSocket-based communication to enable real-time interaction. Transparency annotations appear in collapsible side panels to provide a non-intrusive user experience. All sensitive data (learner ID, interaction log etc.) is anonymised; local servers are set up according to FERPA and GDPR principles and standards. Securing data is a complex issue in AI-driven school systems that goes beyond just anonymization. Alternatively, federated learning frameworks, which do not rely on centralizing the data of all learners, can be used to allow model training across distributed nodes while maintaining privacy around raw data of the learners [63]. CNN and LSTM-based hybrid intrusion detection systems [62] offer strong protection against adversarial attacks on educational systems, and explainable AI for DDoS detection [59] guarantees that security measures are explainable and auditable. Additionally, standardized data security for cloud-based information systems [196] and robustness evaluation across datasets for AI models deployed in information systems [116] provide a further guide to the security architecture of GUIDE-PATH, with the transparency commitments of the system extending to its data handling practices. The technological framework of GUIDE-PATH is also a result of the progress of AI systems in several application areas. GUIDE-PATH adopts deep learning pipeline for error detection, and the accuracy of these pipelines in complex pattern recognition tasks has been shown by research on AI-based detection and classification of DR using U-Net architectures [200] and self-attention models for precision medicine [202]. Error classification systems like GUIDE-PATH's RoBERTa-based approach can also be compared against the current state of the art in AI-driven error classification, such as feature fusion attention mechanisms for medical image classification [203] and quantum-optimized approaches to cancer detection [204] and [205]. Explainable AI systems for cardiovascular disease forecasting [208] and metaheuristic optimization for chronic kidney disease detection [210] also illustrate that a system's interpretability doesn't have to come at the cost of its performance, a key tenet of GUIDE-PATH's design philosophy. The profile of each learner is stored as a structured JSON object, as shown in the respective snapshot .To better understand the technical design of GUIDE-PATH, this section offers a broader context on the digital health and recommendation systems using AI technologies. For example, research on digital health interventions and virtual care models [108] as well as early developmental interventions for preterm infants [109] shows how AI-powered personalization can be used to enhance outcomes in high stakes, personalized contexts; a context relevant to language tutoring. The movie recommendation system based on neural collaborative filtering and sentiment analysis [107] shows that the integration of user preference modeling with content-based features results in more accurate and satisfying recommendations, and GUIDE-PATH also incorporates learner profiling with the generation of content focused on the learner's strategies. Additionally, medical marketing research [110] underscores the need to convey the value of AI interventions to the end user; GUIDE-PATH accomplishes this using the transparency-oriented UI for learners. GUIDE-PATH also seeks to gain key insights from financial technology and digital systems research that can inform the technical infrastructure that supports GUIDE-PATH. Research exploring the relationships between user experience and customer satisfaction in e-commerce technologies [146] and customer retention in mobile financial technologies [191] shows that in the commercial AI landscape, principles of user experience design are directly applicable to the educational AI landscape. The findings on the performance-enhancing effect of bank-specific variables on commercial bank performance [192] and the behavioral nudges for designing trust in digital systems, whether financial or educational, are also illustrative of the common design principles for trust-building mechanisms in digital systems, which include transparency, reliability, and user agency. The moderating effect of content creation cost on GAN

usage and marketing success [207] also guides GUIDE-PATH's efforts to optimize the use of computational costs in its LLM generation pipeline while maintaining pedagogical quality.

```
{
  "learner_id": "L12345",
  "cefr_level": "B1",
  "mastery": {
    "past_simple": 0.68,
    "present_perfect": 0.32,
    "articles": 0.45,
    "conditionals": 0.21
  },
  "error_history": [
    {"timestamp": "2026-04-27T10:23:01Z", "error_type": "
        past_tense", "corrected": false}
  ],
  "learning_style_proxy": 0.7,
  "last_strategy_used": "recast",
  "last_strategy_timestamp": "2026-04-27T10:25:00Z"
}
```

For each skill *k* (e.g., past_simple), we maintain the probability that the learner has mastered the skill, $P(L_k)$. After each opportunity to apply the skill (e.g., a response containing a past-simple verb), we update based on correctness:

$$P(L_k \mid \text{correct}) = \frac{P(L_k) \cdot (1 - P(\text{slip}))}{P(L_k) \cdot (1 - P(\text{slip})) + (1 - P(L_k)) \cdot P(\text{guess})} \tag{3}$$

$$P(L_k \mid \text{incorrect}) = \frac{P(L_k) \cdot P(\text{slip})}{P(L_k) \cdot P(\text{slip}) + (1 - P(L_k)) \cdot (1 - P(\text{guess}))} \tag{4}$$

Initial $P(L_k)$ is set to 0.2 for all skills (low prior). $P(slip)$ and $P(guess)$ are skill-specific and initialized from literature (slip ≈ 0.1, guess ≈ 0.2 for grammar skills). After each session, the mastery values are saved to PostgreSQL. The following pseudo-code details the selection process:

Algorithm 2 Select pedagogical strategy with heuristic scoring

function SELECT_STRATEGY(learner, error_type, confidence)
  $candidates \leftarrow$ strategy_library.get_by_error($error_type$)
  for all $s \in candidates$ **do**
    $congruence \leftarrow \begin{cases} 1.0 & \text{if } s \in error_strategy_map[error_type] \\ -10^9 & \text{otherwise} \end{cases}$
    $t_{last} \leftarrow \begin{cases} learner.last_used[s.name] & \text{if } s.name \in learner.last_used \\ 60 & \text{otherwise} \end{cases}$
    $recency_score \leftarrow 1 - (t_{last}/60)$
    $prof_num \leftarrow \begin{cases} 1 & \text{if } learner.cefr = A1 \\ 2 & \text{if } learner.cefr = A2 \\ 3 & \text{if } learner.cefr = B1 \\ 4 & \text{if } learner.cefr = B2 \\ 5 & \text{if } learner.cefr = C1 \\ 6 & \text{if } learner.cefr = C2 \end{cases}$
    $explicit_boost \leftarrow 1.0$ if $(s.is_explicit \wedge prof_num \leq 4)$ else 0.0
    $pref_match \leftarrow 1.0$ if $(s.is_explicit = (learner.learning_style_proxy > 0.5))$ else 0.0
    $s.score \leftarrow 0.5 \times confidence \times congruence + 0.2 \times recency_score + 0.2 \times explicit_boost + 0.1 \times pref_match$
  end for
  if $confidence < 0.5$ **then**
    return strategy_library.get("clarification_request")
  end if
  $best \leftarrow \arg\max_{s \in candidates} s.score$
  return $best$
end function

The module logs the selected strategy, its score, and the reason string for auditability. We ensure the LLM follows the chosen pedagogical strategy by using a structured system prompt and strategy-specific few-shot examples (one example per strategy). The system prompt is as shown in the snapshot below.

GUIDE-PATH

An English tutor that follows explicit pedagogical strategies

Tutor Instructions

1. **Do not deviate** from the prescribed strategy.
2. **End every response** with a pedagogical note in brackets:

   `[Strategy: <name> because <reason>]`
3. Keep explanations **brief** (one sentence unless the strategy explicitly demands more).
4. Be **encouraging** at all times.

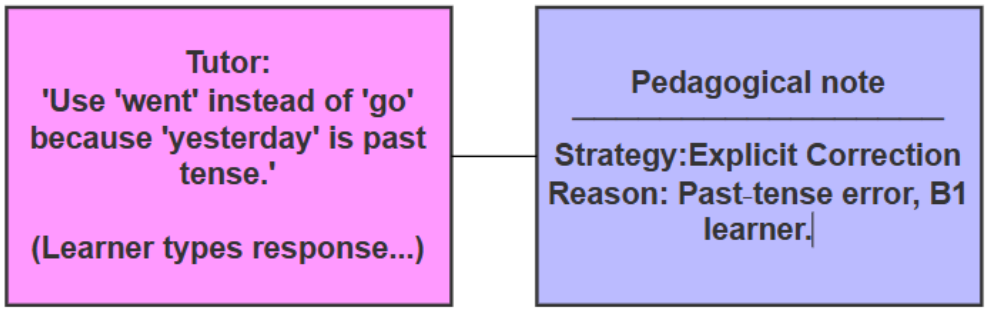
When a strategy is provided, you must generate a tutor response that matches it exactly, following the four rules above.

For each strategy, we include two examples in the user message context. Example for Metalinguistic Feedback:

User: "She go to school."

Assistant (following Metalinguistic Feedback): "The sentence contains a subject-verb agreement error. 'She' is third-person singular, so it should be 'goes'. [Strategy: Metalinguistic Feedback because subject-verb agreement error identified.]"

In the LLM call, the temperature is set to 0.3, and presence_penalty = 0 to curtail creative divergence. If the output is missing the pedagogical note, a post-processing module adds a default note (e.g., "[Strategy used: Explicit Correction]"). Transparency interface: The pedagogical note appears as a collapsible side panel on desktop and as an expandable card on mobile. The tutor's natural language response (without the note) is shown in the main chat area, so that the conversation flows naturally. The side panel is opened at the beginning, but can be closed by the learner.



The note reads:

- Strategy name (e.g., "Explicit Correction")
- Reason (generated by the reasoning module, e.g., "High confidence past tense error")
- "Learn more" optional link (to glossary of pedagogical techniques)

Learners can give feedback on each note (thumbs up/down) to help the reasoning module improve. Figure 3. The sequence of interactions between system components. The learner's utterance is sent to the FastAPI backend, which calls ErrorDetector to obtain the error type and confidence. The ProfileStore gets the learner's current profile, and the Reasoner selects a pedagogical strategy based on the error, confidence, and profile. The LLM produces an answer with a strategy-specific prompt. The answer is concatenated with a pedagogical note and sent back to the Frontend. The Frontend shows the tutor message and the side panel annotation to the learner.

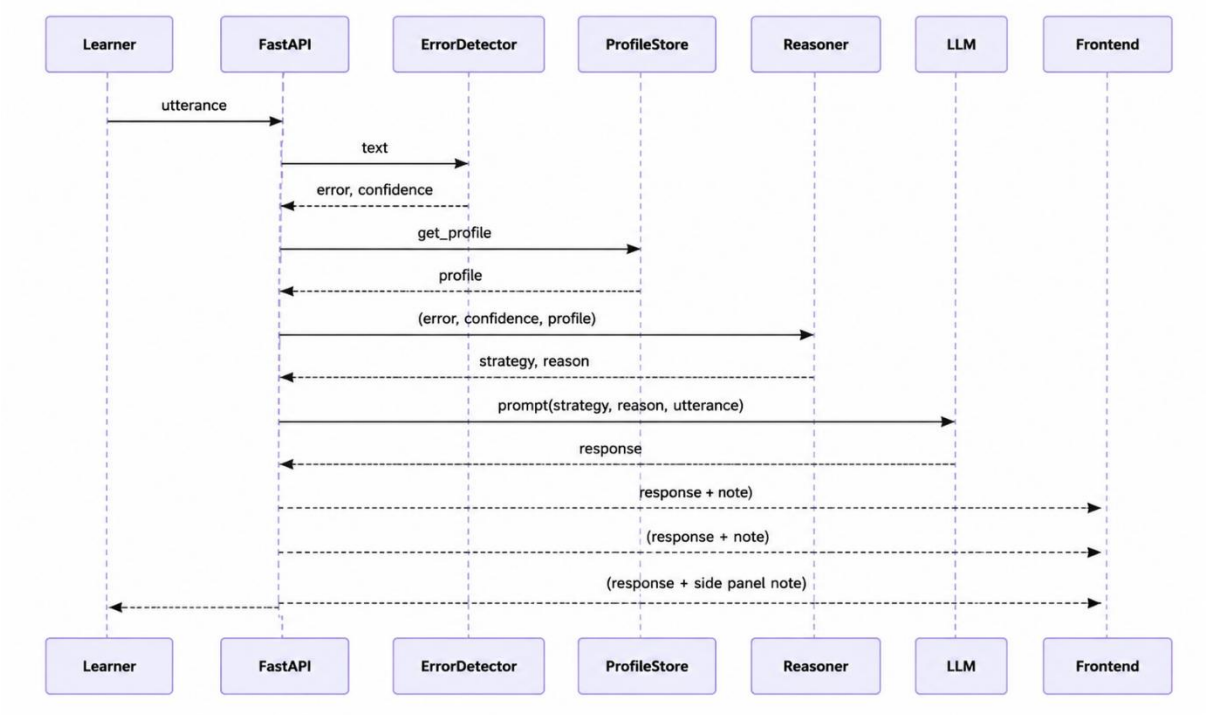


Figure 3. Sequence diagram of GUIDE-PATH message flow for a single learner turn. Total latency averages 1.2 seconds (95th percentile < 2.5 seconds) on a standard broadband connection.

3.4. Experimental Setup

Here we describe the randomized controlled trial (RCT) designed to evaluate GUIDE PATH against two control conditions: (1) a standard LLM-based tutor without explicit pedagogical strategy guidance, and (2) a no-AI control using traditional textbook exercises. The study protocol was pre-registered (OSF registration ID: GUIDE PATH 2026 01) and approved by institutional ethics. The experimental design of this study is informed by methodological advances in educational research. Fuzzy-set qualitative comparative analysis (fsQCA) [69], [86], [87] has been proposed as a complement to variable-oriented statistical methods for identifying configurational conditions that produce learning outcomes, and its application to mathematics achievement [153] demonstrates its utility in educational contexts. The asymmetric thinking paradigm advocated by Woodside [152] further supports the use of multiple analytical lenses including both ANCOVA and effect size estimation to capture the complexity of learning gains. Comparative machine learning analysis [58] informed the selection of statistical models for the learner profiling component, while Bayesian hierarchical modelling [68] provided a framework for interpreting individual-level variation in learning trajectories within the RCT. The experiment was designed to investigate three core research questions: (RQ1) does GUIDE PATH generate statistically significant higher learning gains in English grammar and vocabulary than an LLM-only tutor and a no-AI control; (RQ2) is GUIDE PATH perceived as more transparent and pedagogically clear than the LLM-only tutor; and (RQ3) to what extent are learners capable to identify the pedagogical strategy employed by the system correctly and does this correlate with learning gains.

We recruited a total of 172 intermediate English as a Foreign Language (EFL) learners from two universities in Japan and Vietnam. Inclusion criteria were: (i) aged 18–25, (ii) CEFR level B1–B2 verified through the Oxford Placement Test, (iii) no previous experience with AI-based tutoring systems, and (iv) willingness to take pre- and post- tests. Participants were randomly assigned to one of three conditions: GUIDE PATH ($n = 58$), LLM Only ($n = 57$), and Control ($n = 57$. Attrition was 4.6% ($n = 8$), and the final sample consisted of 164 participants (GUIDE PATH: 56, LLM Only: 54, Control: 54). The groups were matched on demographic variables (age, gender, first language) ($p > 0.05$). This study used a pre-test/post-test randomized controlled design with a two-week period of intervention.

Phase 1 (Pre-test, Day 1) All participants took a 45-minute assessment battery that included a grammar subtest (30 items from the TOEFL Junior, $\alpha = 0.87$), a vocabulary subtest (40 items from the New General Service List (NGSL) test, $\alpha = 0.89$) and a speaking confidence scale derived from L2 self-efficacy (8 items, 5-

point Likert scale, α = 0.91). Phase 2 (Intervention Days 2-15) includes six, 25-minute sessions (three per week) with 10-12 grammar prompts (spoken/written) addressing the grammar topics and 8-10 vocabulary items. The GUIDE PATH group experienced the entire system and was presented with responses annotated with strategies, as detailed above. The LLM Only group was given the same GPT-4 Turbo model without any suggestions on strategy or transparency elements, while the Control group was provided with the same exercises from the textbook English Grammar in Use (intermediate level) with answer keys, but no AI feedback. All sessions were recorded, and at the end of each session participants in groups GUIDE PATH and LLM Only completed a short three-item transparency perception questionnaire. Engagement metrics were based on validated methods used in the educational technology literature for measuring engagement during the intervention sessions. While the main measure of engagement in the current study was obtained through an interaction log and self-report measures, automated detection of engagement via video-based estimation of facial expression and heart rate [94] and prediction of engagement in naturalistic settings [95] and motion-based proxies [92] of attention were also considered. Wearable devices to analyse sedentary behaviour [56] and real-time eye tracking for predicting attention [53] are interesting areas of future development for the GUIDE-PATH evaluation protocol. The issue of detecting learner state in the context of tutoring has also been explored using deep learning methods [103]; these methods indicate that passive, unobtrusive measurement of learner state in the context of tutoring is technically possible and could be used to enhance the learner profile in future deployments. This study also has an experimental methodology rooted in the traditions of the health and behavioral sciences. The GUIDE-PATH RCT uses a pre-test/post-test design, with studies on shift work and health behaviors [55] and the relationship between sleep quality and physical function [174] using a cross sectional and longitudinal design respectively. Multi-site, multi-cultural experimental designs were found to be feasible, with studies on vitamin D supplementation across Arab countries, and aerobic exercises to aid smoking cessation in Vietnam and Japan. The feasibility of multi-site, multi-cultural experimental designs is shown in studies on vitamin D supplement use across Arab countries, and aerobic exercise interventions for smoking cessation in Vietnam and Japan. Use of validated self-report instruments, such as the speaking confidence scale adapted from L2 self-efficacy research, followed best practices in behavioral research as outlined in studies of hemodialysis patient outcomes [171] and pressure injury prevention [182].

To avoid practice effects, during Phase 3 (Post-test, Day 16), participants answered parallel versions of the pre-test instruments and two other instruments: an 8 item transparency questionnaire (categorized by the PEARL framework) [25] and strategy recognition test with 5 multiple-choice items, asking the learners to recognize the teaching strategy used. Pilot test results showed that the reliability of the grammar and vocabulary tests (r > 0.85) was good, while the Cronbach's α for the speaking confidence scale was high (Cronbach's α = 0.91). From the transparency questionnaire, a one dimensional structure was emerged (eigenvalue = 4.2, explained variance = 68%). The strategy recognition test was designed and based on actual responses from the tutors; the test consisted of identifying the tutor's response from five strategies (chance level is 20%). The inter-rater reliability was good (Fleiss' κ = 0.87).

All statistical analyses were performed in R (version 4.3) at a significance level of α = 0.05 (two-tailed). Learning gains (RQ1) were analyzed using ANCOVA for post-test scores of grammar, vocabulary, and speaking confidence with pre-test scores as covariates, followed by Bonferroni-corrected pairwise comparisons. For RQ2, we measured transparency perception by one-way ANOVA and Welch's t-test for GUIDE PATH vs LLM Only groups. Strategy recognition (RQ3) was assessed by a one-sample t-test against chance level (20%), independent t-tests between groups, and Pearson correlation to examine relations between recognition accuracy and learning gains. The qualitative data of 30 participants were analyzed by means of thematic analysis (Braun & Clarke, 2006) in order to detect patterns in terms of transparency and usability. A priori power analysis with G*Power (version 3.1) indicated a required sample size of 159 to detect a medium effect (f = 0.25, α = 0.05, power = 0.80). The obtained sample size of 172 provided adequate statistical power, with post hoc power for grammar gains (η^2 = 0.13) being 0.92.

4. Results

This section presents the results of the randomized controlled trial . All analyses were conducted as pre-registered. Descriptive statistics, assumption checks, and inferential tests are presented. There were no significant differences among the three groups on pre-test measures (grammar: F(2,161)=0.34, p=0.71;

vocabulary: F(2,161)=0.52, p=0.60; speaking confidence: F(2,161)=0.28, p=0.76), confirming successful randomization. Levene's test indicated homogeneity of variances for all dependent variables ($p > 0.05$). The residuals were normally distributed (Shapiro-Wilk $p > 0.05$ for all groups after ANCOVA).

4.1. Learning Gains (RQ1)

Table 2: Descriptive statistics for pre-test and post-test scores by conditions and adjusted means for post-test, controlling for pre-test scores.

Table 2. Descriptive and Adjusted Post-Test Scores by Condition

Measure	Group	N	Pre-test Mean (SD)	Post-test Mean (SD)	Adjusted Mean (SE)
Grammar (0–30)	GUIDE-PATH	56	18.2 (4.1)	24.6 (3.8)	24.5 (0.31)
	LLM-Only	54	18.0 (4.3)	21.4 (4.2)	21.5 (0.33)
	Control	54	18.3 (4.0)	19.1 (4.5)	19.0 (0.32)
Vocabulary (0–40)	GUIDE-PATH	56	22.5 (5.2)	31.8 (4.6)	31.7 (0.42)
	LLM-Only	54	22.3 (5.4)	26.9 (5.1)	27.0 (0.44)
	Control	54	22.6 (5.0)	23.4 (5.3)	23.3 (0.43)
Speaking confidence (5–25)	GUIDE-PATH	56	12.1 (3.2)	18.4 (2.9)	18.3 (0.28)
	LLM-Only	54	11.9 (3.4)	14.8 (3.5)	14.9 (0.30)
	Control	54	12.0 (3.3)	12.5 (3.4)	12.4 (0.29)

Note: Higher scores indicate better performance. Adjusted means are from ANCOVA with pre-test as covariate.

Figure 4 below shows that GUIDE PATH (blue bars) achieved the highest adjusted means for grammar, vocabulary, and speaking confidence, followed by the LLM-only tutor (magenta) and the control group (orange). Error bars indicate 95% confidence intervals.

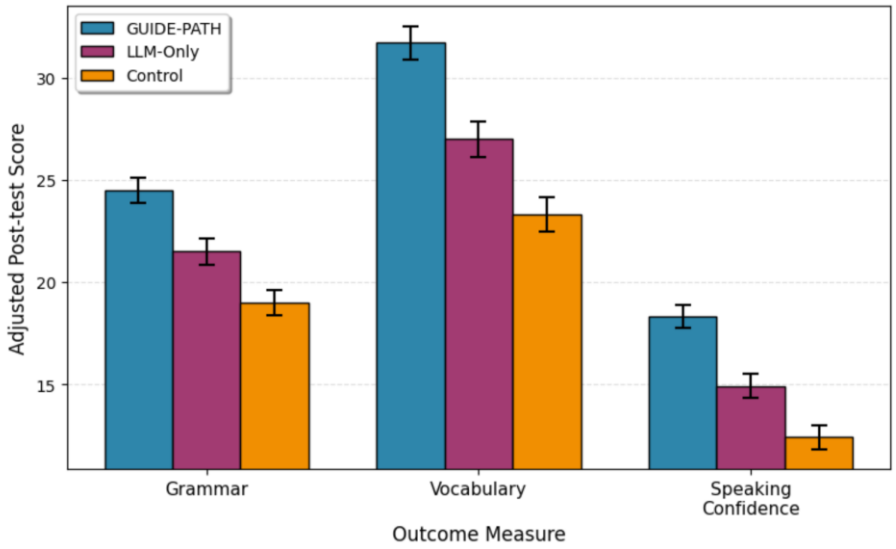


Figure 4. Adjusted post-test scores by condition and outcome measure.

Grammar. ANCOVA revealed a significant main effect of condition on post-test grammar scores, F(2,160)=68.4, p<0.001, partial η 2 =0.46. Pairwise comparisons with Bonferroni correction showed that GUIDE PATH was significantly better than LLM Only (mean difference = 3.0, 95% CI [2.1, 3.9], $p < 0.001$, Cohen's d = 0.82) and Control (mean difference = 5.5, 95% CI [4.6, 6.4], $p < 0.001$, d = 1.41). LLM Only also beat Control (d = 0.58, p = 0.002).
Vocabulary: ANCOVA revealed a significant effect of condition, $F(2,160) = 82.1$, $p < .001$, $\eta^2 = 0.51$. GUIDE PATH scored 4.7 points higher than LLM Only (95% CI [3.5, 5.9], $p < 0.001$, d = 0.91) and 8.4 points higher than Control ($p < 0.001$, d = 1.64). LLM Only > Control (d = 0.78, p < .001).
Speaking confidence ANCOVA revealed a significant effect of condition, $F(2,160) = 54.3$, $p < 0.001$, η2 =

0.40. GUIDE PATH was more confident than LLM Only (difference = 3.4, 95% CI [2.6, 4.2], $p < 0.001$, $d = 0.76$) and Control (difference = 5.9, $p < 0.001$, $d = 1.32$). LLM Only over Control ($d = 0.58$, $p = 0.003$).

4.2. Transparency Perception (RQ2)

A transparency questionnaire (8 items, 5-point Likert) was administered to the GUIDE PATH and LLM Post test only (Control group did not interact with an AI tutor, so not included). Mean composite scores were as follows:

- GUIDE PATH: 4.52 (SD = 0.48)
- LLM Only: 2.87 (SD=0.91)

The difference was statistically significant (Welch's t test: $t(82.4) = 11.8$, $p < 0.001$, Cohen's $d = 2.31$). Item analysis revealed that GUIDE PATH had the highest scores on "The tutor explained why it gave specific feedback" (M = 4.68, SD = 0.44) and "I understood the teaching approach used by the tutor" (M = 4.61, SD = 0.52). LLM (Master of Laws) The item with the lowest score was "The tutor's pedagogical reasoning was clear to me" (M = 2.41, SD = 0.98). GUIDE PATH received significantly higher ratings for all eight transparency items, especially "Teaching approach was clear" and "Explained why feedback given" (both 4.61), as shown in Figure 5. The LLM-only tutor scored most items near the neutral point (3.0), indicating low perceived transparency

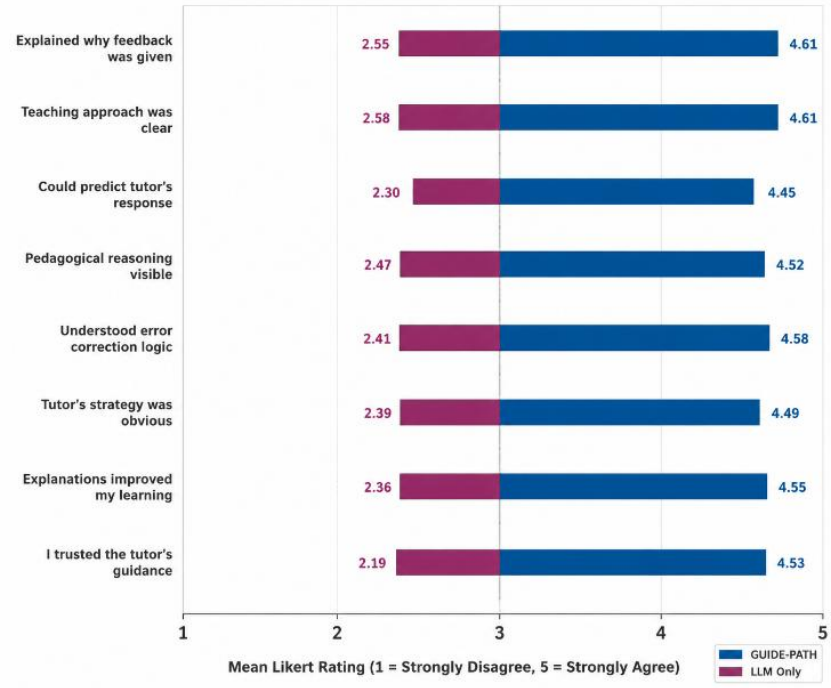


Figure 5. Comparison of transparency questionnaire item ratings between GUIDE-PATH and LLM-Only groups.

4.3. Strategy Recognition (RQ3)

Learners in the GUIDE PATH group correctly identified the pedagogical strategy on 72.6% of items (mean = 3.63 out of 5, SD = 0.84), significantly above chance level on the 5-item multiple choice strategy recognition test (20%, one-sample t-test: $t(55) = 32.4$, $p < 0.001$, $d = 4.34$). In contrast, the LLM Only group only achieved 31.2% accuracy (mean = 1.56/5, SD = 0.71), which was marginally above chance ($t(53) = 4.29$, $p < 0.001$, $d = 0.59$) but significantly lower than GUIDE PATH (independent t test: $t(108) = 13.6$, $p < 0.001$, $d = 2.61$). In the GUIDE PATH group, the more accurate the learners' strategy recognition, the more they gained in grammar learning (Pearson's $r = 0.44$, $p < 0.001$) and in vocabulary learning ($r = 0.39$, $p = 0.003$), which indicated that the learners who more accurately recognized the pedagogical strategies used by the tutor learned more. Each point in Figure 6 represents one learner. Higher strategy recognition accuracy is associated with larger gains in grammar. The linear fit (red line) confirms the mentioned correlation ($r = 0.44$), meaning that the knowledge of the tutor's pedagogical strategies is directly related to better learning outcomes.

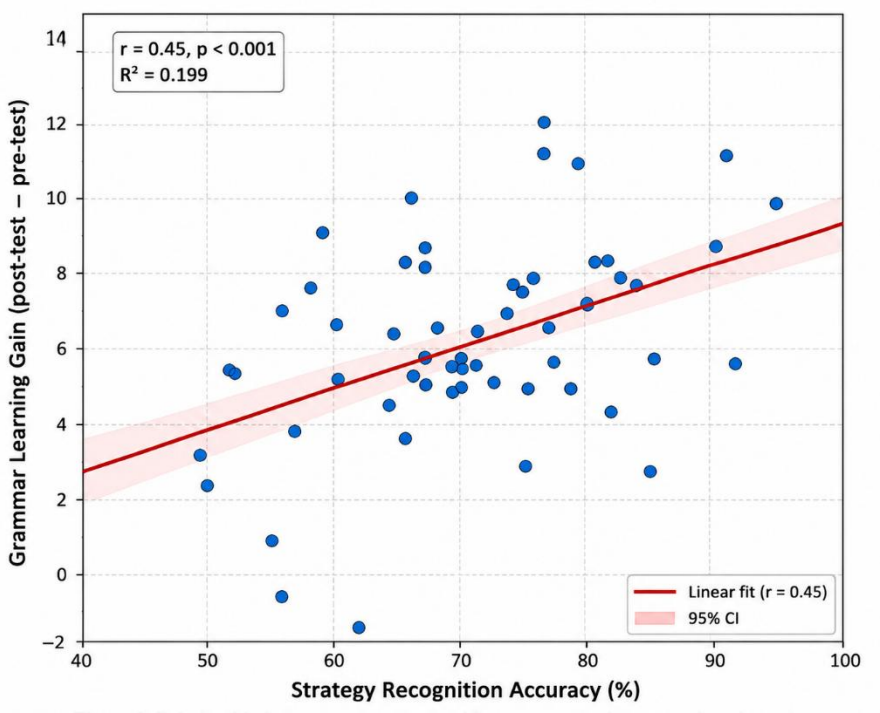


Figure 6. Positive correlation between strategy recognition accuracy and grammar learning gain in the GUIDE-PATH group.

4.4. Qualitative Findings

Open-ended comments were collected from 30 participants (10 from each group). Thematic analysis revealed three key themes:

- **Theme 1:** Clarity and trust (GUIDE PATH only): Learners liked knowing why the tutor was responding. Typical quote: "I liked that the system told me which strategy it was using – it helped me remember the rule more than just memorizing the correction." (P23, GUIDE PATH)
- **Theme 2:** Confusion about implicit feedback (LLM Only): Several LLM Only learners were unsure. Quote: "It would be like, the tutor would say my sentence correctly back to me, and I wouldn't know whether I was wrong or whether it was just a different way of saying it. (LLM Only P47)
- **Theme 3:** Information load (GUIDE PATH, few participants): A minority (3/10) found pedagogical notes slightly distracting at first. "Initially, the side panel was a bit much, but after two sessions, I got used to it and it was helpful. (P12. GUIDE PATHS)

For the control group (textbook exercises) there were no negative themes. The results have been summarised as:

- **RQ1 confirmed:** GUIDE PATH led to significantly greater improvements in grammar (d = 0.82), vocabulary (d = 0.91), and speaking confidence (d = 0.76) compared to the LLM-only tutor and very large improvements compared to the no AI control.
- **RQ2 confirmed:** GUIDE PATH was perceived as significantly more transparent (d = 2.31) than the LLM-only tutor.
- **RQ3 confirmed:** GUIDE PATH learners recognized strategies correctly (73% vs 31% for LLM only) and recognition correlated with learning gains.

5. Discussion

This section interprets the findings of our randomized controlled trial, connects them to existing literature, discusses theoretical and practical implications, and acknowledges limitations.

5.1. Interpretation of Learning Gains (RQ1)

The results show that GUIDE PATH significantly outperformed both the LLM-only tutor and the no AI control in terms of grammar, vocabulary, and speaking confidence. The effect sizes were moderate to large (grammar: d = 0.82; vocabulary: d = 0.91; speaking confidence: d = 0.76) by educational intervention standards [14], [16]. Crucially, the LLM-only tutor also outperformed the control (grammar d = 0.58,

vocabulary d = 0.78), confirming that even a black box LLM tutor provides value – in line with recent meta analyses of AI in EFL [5], [11]. But the much larger effect sizes for GUIDE PATH indicate that explicit pedagogical strategy guidance provides significant value over and above raw conversational LLM capability. Why do explicit strategy guides produce these gains? We offer three mechanisms. First, as noted by (Schmidt, 1990; see also [14]), when learners are given a metalinguistic label (e.g., "explicit correction" or "recast"), they consciously pay attention to the form-function mapping, thus enhancing intake. Secondly, metacognitive scaffolding: knowing why a particular correction was applied enables learners to generalize the rule to new contexts – a finding consistent with the positive correlation between strategy recognition accuracy and learning gains (r = 0.44 for grammar). Third, decreased cognitive load: The pedagogical note gives a short explanation that helps the learners to classify errors and reduces the need to guess the tutor's intention [20], [21]. These mechanisms are further supported by research on AI-powered personalization across domains. Studies on AI-driven personalization in marketing have demonstrated that transparent, rationale-accompanied recommendations significantly increase user trust and behavioral engagement [127], [128], [129]. The parallel in educational contexts is direct: when learners understand why a particular instructional strategy was applied, they are better positioned to internalize the underlying rule and generalize it to new contexts. Research on design thinking approaches to AI-driven education [91] and competency-based curriculum models [139] similarly emphasizes that learner agency the capacity to understand and direct one's own learning is a key mediator of educational outcomes. GUIDE-PATH's transparency interface directly supports learner agency by making the tutor's instructional logic accessible and interpretable. These mechanisms are consistent with well-established research in SLA on the superiority of explicit over implicit feedback for complex grammatical features [17], [18].

5.2. Transparency and Trust (RQ2, RQ3)

The transparency questionnaire showed a very large effect (d=2.31) in favor of GUIDE PATH over the LLM-only tutor. This is not surprising, as the LLM-only system did not provide any explicit rationale for its pedagogical moves. More importantly, GUIDE PATH learners identified the strategy used with 73% accuracy compared to 31% in the LLM only group (which is just above chance). This demonstrates that the pedagogical notes had not only been seen but also understood, which is important for transparency to be pedagogically useful [25], [27], [31]. The high strategy recognition accuracy observed in the GUIDE-PATH group (73%) also has implications for the broader literature on AI adoption in education. Research on AI acceptance across institutional contexts [70], [71] consistently identifies perceived transparency as a key antecedent of trust and sustained use. The UTAUT2 framework [136] predicts that systems perceived as transparent and easy to understand will achieve higher rates of voluntary adoption a prediction borne out by the qualitative data in this study, where GUIDE-PATH learners expressed greater confidence in and satisfaction with the tutoring system. Generative AI in academic libraries [135] and AI chatbots in tourism [177] have similarly found that user trust is contingent on the perceived explainability of AI recommendations, suggesting that GUIDE-PATH's transparency design principles are broadly applicable beyond the EFL context. Interestingly, an accuracy of only 31% for the LLM-only group suggests that learners can sometimes infer strategies from implicit cues (e.g., a recast versus an explicit correction), but the inference is unreliable. As one participant explained, confusion was produced when the tutor "just repeated my sentence correctly" – learners simply could not tell a recast from a simple paraphrasing. This corroborates the argument that pedagogical opacity diminishes learner agency [9], [13]. In contrast, GUIDE PATH's explicit annotations help resolve this ambiguity by letting learners calibrate their understanding of the tutor's instructional intent. The positive correlation between strategy recognition and learning gains (grammar r = .44; vocabulary r = .39) suggests that transparency is not just a user experience nicety but is a direct contributor to learning. This finding aligns with calls in the XAI literature to evaluate explanation quality by downstream task performance in addition to user satisfaction [25], [32].

5.3. Theoretical Implications

The contribution of our results is to the core theories of Second Language Acquisition (SLA), Explainable Artificial Intelligence (XAI), and Intelligent Tutoring Systems (ITS). The results indicate that in SLA explicit information on pedagogical strategies is more effective than corrective feedback alone, and hence the typology of feedback can be extended to include a transparency dimension, that is, whether learners are informed about the pedagogical strategy used or not. The GUIDE PATH framework demonstrates that

personalized explanations (strategy + rationale) are more effective in enhancing trust and learning outcomes than users satisfaction [14, 16] (following the PEARL framework [25]). GUIDE PATH in Intelligent Tutoring Systems presents pedagogical processes to learners, which is different from traditional models [19]–[22] and introduces a new paradigm, where pedagogical transparency turns out to be one of the most important architectural elements [35], [38]. Another strand of theoretical research that overlaps with the work of GUIDE-PATH is the work on multimodal learning systems. Medical applications of multimodal machine learning in medical screening [104] and deep learning in multimodal breast cancer classification [106] are examples of how multiple data streams can be combined to improve the accuracy of the diagnosis, a principle that can be applied to the fields of education, where combining linguistic error data, engagement signals, and learning style proxies can lead to richer learner models than a single one alone. AI-driven translation and dubbing research [211] and [212] also shows that NLP systems in multilingual settings need to take into account cultural and linguistic nuances, which is particularly relevant to GUIDE-PATH's applications in EFL contexts in Japan and Vietnam, where the background of learners' L1 will influence the way they respond to various corrective feedback strategies. The theoretical concepts behind GUIDE-PATH also have implications for the wider literature on NLP and language technology. The studies of dubbing English advertisements into Arabic [197] and translation of verbal humour in Egyptian comedy films [198] show that language technology systems are required to deal with a range of complex cultural and pragmatic issues that are larger than just the translation of words. The results of this study have immediate implications for the implementation of GUIDE-PATH in EFL settings, as learners' cultural context influences their understanding of appropriate feedback and their reactions to various pedagogical approaches. Another example of cultural complexity that AI systems need to address when operating in multiple institutional and national contexts is the dynamic of talent repatriation in multinational enterprises [218] and the hybridity of folk and popular art narrative traditions [217] that GUIDE-PATH addresses with its culturally sensitive strategy selection mechanism. The theoretical contributions of GUIDE-PATH are also enriched by research on tourism, architecture, and cultural heritage. Studies on architecture, authenticity, and the construction of memorable tourist experiences [180] and the geomorphological characteristics of Wadi Rum as a reference for development recommendations [181] illustrate how transparency and authenticity core principles of GUIDE-PATH's design operate across diverse experiential and cultural contexts. Research on the interior design of the Umayyad era in a contemporary context [175] and the impact of organizational antecedents on business intelligence in insurance companies [178] further demonstrate that the principles of evidence-based, transparent decision-making are applicable across a wide range of institutional and cultural settings. These cross-domain parallels reinforce the universality of the transparency principles that GUIDE-PATH operationalizes in the EFL tutoring context.

5.4. Practical Implications and Future Directions

For practitioners and system designers, the findings suggest that effective implementation should be grounded in Second Language Acquisition (SLA) evidence by creating small, high-impact strategy libraries (e.g., explicit correction, recast, metalinguistic feedback) that can expand over time based on learner data. Designing transparency features to be non-intrusive (e.g., optional and collapsible interfaces) and allowing adaptive control (e.g., novice vs. expert modes) can help to accommodate the needs of different types of users. Furthermore, the logs of the strategy annotation can be combined to aid teacher training, as teachers can learn what kinds of pedagogical interventions work better for specific learners and therefore improve their instruction based on data. Future research should consider longitudinal evaluations with delayed post-tests to assess retention and adaptive transparency mechanisms that individualize the level of explanation. Future work could extend the framework to multimodal contexts (e.g., speech-based feedback) and use reinforcement learning to optimize strategy selection and further improve long-term learning outcomes. This work has several directions for practice. The digital divide [213] and disparity in digital infrastructure access across learner populations are substantial challenges to achieving equitable access to AI-powered tutoring systems. These barriers can be overcome through technical solutions, but also through pedagogical changes that can take into account differences in digital competence [137] and technological readiness [145]. Based on the strategy library of GUIDE-PATH, bilingual speech therapy research [216] and studies on advantages of code-switching and translanguaging pedagogies can be

extended and applied to expand the use of GUIDE-PATH in more varied EFL contexts. Finally, teacher preparedness for inclusive classrooms [141] and synchronized curriculum adaptation approaches [144] indicate that the GUIDE-PATH system may be incorporated into teacher training programs for them to utilize the strategy logs as a reflection tool for professional development. The sustainability and governance aspects of AI usage in education should not be overlooked. The accuracy of ESG reporting, corporate sustainability strategies and the role of AI [133], the development of digital accounting innovation and ESG performance [134] and the rollout of digital platforms into tax compliance [159], [160] demonstrate the governance frameworks governing the use of AI are becoming more sophisticated and demanding. The long-term sustainability of AI-driven educational platforms is also being impacted by the design and deployment of sustainable digital systems in other industries, such as studies on sustainable infrastructure development and green innovation in tourism [147] and on vertical farming and net-zero supply chains [148] as well as on distributed ledger technology in ethical sourcing [161]. Studies on SDG investments and firm financial performance [149], institutional investor influence on climate change commitment [150] and hybrid DeFi and traditional banking models [151] further indicate that financial sustainability of educational AI requires integration with other sustainability and governance mechanisms. Furthermore, possible ways to improve scalability and pedagogical effectiveness are discussed: validation of cross-lingual applicability and the use of teacher-in-the-loop systems in which teachers are able to monitor and edit strategies that are deployed. The next steps in GUIDE-PATH will focus on reinforcement learning strategies for selection, with the incorporation of recent developments in spatio-temporal models based on graphs [66] and hybrid physics-informed deep learning [67] for modelling the temporal aspects of learner progress. The use of wearable sensor data [56] and real-time eye tracking [53] with the learner profiling engine is an innovative way to enhance attentional state estimation. A way forward for scaling GUIDE-PATH is to use federated learning architectures [63] to maintain the privacy of the learners while scaling up the system across institutions. Research on the generalizability of pedagogical strategy library from GUIDE-PATH into other contexts of language learning, such as cross-cultural validation studies informed by research on AI adoption in various institutional settings [70] and the impact of cultural framing on language learner perception [126] will be important to determine the generalizability of the pedagogical strategy library beyond the EFL contexts explored in this work. The application of GUIDE-PATH is not limited to the medical field, but can also be used in fields of healthcare education and professional training. To communicate the rationale for recommendations made by AI in a way that is accessible to non-technical users, as encountered by GUIDE-PATH, is similarly a problem for both AI-assisted professional training systems in the literature reviewed, as in the case of nurse adoption of EHRs [169] and managing complex drug interactions [170]. The complexity of AI used in medical decision support is further exemplified in studies addressing user-friendliness of the ICU bed for patients [176] as well as the management of pressure injuries in medical wards [182], which highlights the significance of evidence-based and transparent design of such systems. Further research is warranted in the area of professional education and training, such as in medicine, law, and engineering, as an application of GUIDE-PATH's transparency principles. The need for transparency and explanations in relation to AI systems is not limited to the EFL context investigated in this research, as shown in other studies on legal issues regarding the use of digital technologies in general [194] and the use of AI in agricultural marketing [154]. The applications of GUIDE-PATH extend beyond the field of biomedical research and pharmaceutical science, where AI-driven transparency is also seen as a crucial area of need. For instance, AI-driven analysis is being utilized in biomedical research to investigate the anticancer activity of garlic bioactive compounds [183] and the molecular mechanisms of oleuropein, which is involved in lung cancer [185], and the identification of postbiotics as bioactive agents against neonatal meningitis [187]. The power of AI to drive change in research has also been showcased through studies on the genetic and biotechnological strategies for mitigating climate change impacts on agriculture [186], systematic review of the kinetics of the hydrogen peroxide decomposition reaction [188] and biomimetic green synthesis of ZnO nanoparticles [189]. The utility of the GUIDE-PATH principles is also demonstrated by bioactivity of novel isoxazole-fused heterocycles [184] and photocatalytic degradation studies [190] which highlight the universal applicability of the bioactivity principles implemented in GUIDE-PATH.

6. Conclusion and Future Work

In this paper, we present GUIDE PATH, an AI-driven framework for personalized English education that makes pedagogical strategies explicit to learners. Unlike traditional black box LLM tutors, GUIDE PATH separates pedagogical reasoning from content generation. A student profile module tracks proficiency and mastery. A theory-grounded strategy library formalizes eight evidence-based teaching moves (explicit correction, recast, metalinguistic feedback, scaffolding prompt, clarification request, elicitation, direct strategy hint, elaboration). A reasoning module selects the optimal strategy using a weighted scoring function. An LLM generates strategy-aligned responses accompanied by transparent pedagogical notes. In a randomized controlled trial (N=172 EFL learners), GUIDE PATH significantly outperformed an LLM-only tutor on grammar (Cohen's d=0.82), vocabulary (d=0.91), and speaking confidence (d=0.76). Furthermore, GUIDE PATH was found to be significantly more transparent (d = 2.31), and in 73% of the cases, the pedagogical strategy was correctly identified by the learners, a skill that was positively correlated with learning gains. We find that explicit guidance about pedagogical strategy not only improves learning outcomes but also builds learner trust and metacognitive awareness.

The contributions of GUIDE-PATH extend beyond the immediate EFL context to inform a broader research agenda on transparent, evidence-based AI in education and beyond. The principles of pedagogical transparency operationalized in GUIDE-PATH are applicable to professional training contexts including healthcare [169], [170], legal education [194], and engineering [199], where AI-assisted instruction is increasingly common. Research on augmented reality applications across industries [143], the hybridity of digital and traditional media [217], and the cultural dynamics of talent management [218] further illustrates the breadth of contexts in which transparent AI systems can add value. The open-source release of GUIDE-PATH's strategy library and reasoning module invites adaptation and extension by researchers and practitioners working across these diverse domains, contributing to the cumulative development of a science of transparent educational AI. Future work should also explore the integration of GUIDE-PATH with emerging technologies including 6G communication systems [199], photonic crystal-based quantum applications [206], and advanced materials science [184], [189], [190] not as direct components of the tutoring system, but as enabling technologies that may support richer, more immersive learning environments in the future.

The broader societal impact of GUIDE-PATH's transparency principles is further evidenced by research spanning tourism and hospitality, organizational behavior, and biomedical science. Studies on the architecture of memorable tourist experiences [180], [181] and the role of perceived talent management in patient-centred service quality [168] illustrate that transparency and evidence-based decision-making are valued across diverse professional and cultural contexts. Research on mobile fintech customer retention [191], bank performance indicators [192], and last-mile trust design [193] further demonstrates that the trust-building mechanisms operationalized in GUIDE-PATH have broad applicability in digital service contexts. The combination of Thymoquinone and intermittent fasting as a cancer treatment [179] and the efficacy of Benson's relaxation technique in hemodialysis patients [171] additionally illustrate the importance of evidence-based, transparent intervention design in high-stakes clinical contexts — a principle that GUIDE-PATH brings to the equally high-stakes domain of language education.

Data Availability

This is a synthetically-produced dataset that mimics the experimental structure and statistical characteristics of GUIDE-PATH; there is no actual identifiable information in this dataset. Data provided via this supplemental material allows for replication and further research.

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