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AI-Augmented Probabilistic Model for EFL Error Analysis: Applying Al Sadr's Inductive Theory to Second Language Learning

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Abstract in English

This study suggests an AI-enhanced probabilistic model for predicting grammatical error frequency in English as a Foreign Language (EFL) academic writing, inspired by the inductive reasoning of Sayyid Muhammad Baqir al-Sadr. Based on Bayesian inference, the model classifies errors into high-, medium-, and low-probability categories using learners' prior data .
This study applied a quasi-experimental design with 100 undergraduate students, comparing AI-assisted feedback (via ChatGPT and Grammarly) with traditional teacher-assisted feedback. Pre- and post-test were conducted across five error types, the model demonstrated high predictive accuracy, with deviations between predicted and observed error frequency rates remaining below ±1.5%. Participants who received AI-assisted feedback significantly reduced high-probability errors by 30%, compared to 20% with teacher-assisted feedback. This result demonstrate the pedagogical effectiveness and scalability of the model. Sadr's inductive logic enriches the Bayesian framework by introducing a logically grounded epistemology for probabilistic inference. This invesgation develops an evidence-based adaptive learning model that links linguistic theory, artificial intelligence, and second language teaching methodology, suggesting a practical applications for AI-enhanced writing and grammar instruction in diverse educational contexts.

Paper Info

Keywords

AI-assisted feedback, probabilistic model, Bayesian model, Al-Sadr's inductive logic, Error prediction, adaptive writing

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1. Introduction

Error analysis (EA) plays a key role in second language acquisition (SLA), It helps teachers and researchers see how learners are developing their language skills and shows where learners make mistakes compared to the target language (Khansir, 2012;

Zhu, 2019). There are several models that try to explain learner errors, like the contrastive analysis hypothesis (CAH), traditional error analysis, and linguistic interference theory. These models have helped a lot in understanding common patterns of mistakes. EA can predict some areas where learners might struggle by looking at differences between their first language (L1) and the target language (L2). But it does not always catch errors that happen naturally in L2 itself, like developmental or internal errors (Richards, 1971; Erdogan, 2005). To deal with this, EA divides errors into interlingual and intralinguistic categories, which helps teachers decide how to respond. Even so, most of these assessments are descriptive. They don't really tell you how likely an error is to happen again (Zhu, 2019; Khansir, 2012). Linguistic interference theory (Selinker, 1972) gives a developmental view, but it also does not provide ways to predict persistent mistakes quantitatively.

The problem with these approaches is that they mostly look backward. They describe errors after they happen but do not help teachers know which errors will come up again which makes it harder to use them for planning lessons in real classrooms, especially with students who make very different kinds of mistakes. Teachers need models that do more than just show what errors exist—they need models that show which ones are likely to keep happening and need more attention.

To fill this gap, this invesgation introduces a Bayesian probabilistic inductive model, inspired by Sayyid Muhammad Baqir al-Sadr's inductive theory (al-Sadr, 1977, 1980). This model uses past learner data to estimate how likely certain grammatical errors are to appear again. It gives a way to predict and adapt teaching strategies. Bayesian inference makes it possible to update error probabilities continuously as new data from learners come in (Tenenbaum et al., 2011; Goldwater et al., 2009). By combining Sadr's ideas with real classroom practice, the model connects logical reasoning with actual teaching.

This approach also fits with modern trends in applied linguistics, which focus on personalized, data-driven learning. It can be used with AI tools and intelligent tutoring systems (Kumar et al., 2020; Griffiths et al., 2008). Predicting which errors are likely to repeat helps teachers focus their instruction better, encourages learners to take responsibility for improving, and reduces the chance that mistakes become habitual. In the end, this provides a practical approach to making language learning both more efficient and more effective.

This investgation addresses the following research questions:

1. What are the most frequent and persistent grammatical errors committed by EFL learners in academic writing?
2. How effectively does the proposed Bayesian-inductive model predict and categorize error types in EFL learners' academic writing?
3. To what extent does AI-assisted feedback reduce the recurrence of high-probability learner errors compared to traditional instructor feedback?

4. What teaching strategies and technological applications can be derived from the model to address high-probability errors in EFL classrooms?

A Bayesian-based probabilistic inductive model outperforms traditional descriptive frameworks in predicting EFL learner mistakes. This approach allows educators and teachers to prioritize high-probability errors and reduce recurrence through targeted interventions based on historical error frequency and learner-specific trends (Wu & Garza, 2014).The investigation aims to develop a statistical framework using a Bayesian probability formula to measure error recurrence likelihood based on learner data. It compares this model with traditional theories like Error Analysis and Contrastive Analysis Hypothesis, and provides data-driven recommendations for teaching strategies based on error probability levels.

2. Literature Review

Traditional Approaches to Error Analysis

Error analysis forms the basis for research into second language (SLA) acquisitions and provides tools to identify, classify and solve student difficulties. Several theoretical frameworks were at the heart of this tradition, including the contrast analysis hypothesis (CAH), the analysis of errors (EA), theories of interligan contact, behaviorism, universal grammar, and cognitive models. Although each structure has contributed in its own way to understand the formation of errors, they all share an important limitation: unpredictability. The Contrastive Analysis Hypothesis (CAH) argues that errors are primarily linked to structural differences between students' first language (L1) and target language (L2). CAH helps to identify phonological and syntactic difficulties such as Arabic speakers' omission of certain English devices, but does not take into account linguistic or development errors. Research shows that rather than many errors arise from L1 interventions, they attempt to assimilate and apply L2 rules (Richards, 1971; Erdogan, 2005).

Error Analysis (EA) was developed to address the shortcomings of CAH by focusing on real learner performance. It distinguishes between interlingual and intralingual errors and provides valuable diagnostic information for classroom instruction. However, EA remains largely descriptive, lacking the statistical tools needed to estimate the likelihood of recurrence or to prioritize instructional interventions (Zhu, 2019; Khansir, 2012).

Interlanguage Theory, introduced by Selinker (1972), conceptualizes learner language as a dynamic, rule-governed system that evolves over time. While this theory offers insight into developmental stages and fossilization, it does not offer predictive metrics for anticipating future errors or customizing feedback.

Behaviorist models emphasize rote learning and error elimination through repetition and reinforcement. Though effective for surface-level corrections (e.g., pronunciation drills), these models overlook the deeper cognitive and developmental factors in SLA (Yang et al., 2022).

Universal Grammar (UG), proposed by Chomsky (1965), maintains that all people have congenital grammatical structures. While this theory explains certain cross linguistic patterns, its abstract nature limits its applicability to classrooms in class individual error correction. While cognitive aproache focus on hypothesis testing and mental rule formation during language acquisition. They help explain overgeneralization (e.g., “childs” for “children”) but often disregard external variables such as instructional methods or feedback, and lack mechanisms for forecasting persistent errors (Richards et al., 1992; Hsu & Chater, 2010).

Despite their contributions, these frameworks remain reactive in nature. None of them incorporate real-time statistical modeling to predict error recurrence or adapt instruction accordingly. This gap has motivated a shift toward probabilistic and computational approaches, which combine insights from linguistics, cognitive science, and artificial intelligence.

Recent research emphasizes the importance of using data-driven models to predict learner difficulties. Bayesian inference, in particular, promotes the continuous updates of probability of error based on observed data (Griffiths et al., 2008; Goldwater et al., 2009). This statistical methodology is particularly effective for addressing dynamic environments with learning that is dependent on time, as the performance of the learner increases over time and the instructional decisions must be continuously altered. Models that follow the Bayesian approach have demonstrated success in a variety of linguistic tasks including grammar induction, speech feedback, and real-time speech generation (Tenenbaum et al., 2011; Ambridge & Lieven, 2011). In EFL context, the model accurately predict high-risk errors (e.g., the use of verbs in the wrong tense, omission of articles), it can also help educators direct their instructional efforts more sparingly, additionally, they can be incorporated into platforms that are powered by AI and have personalized, adaptive feedback for students based on their unique profile of errors (Kumar et al., 2020; Zhang, 2018).

The application of Bayesian inference to English language learning reflects a broader shift in applied linguistics toward evidence-based pedagogy, where teaching strategies are not only grounded in linguistic theory but also extended to learner empirical data. This convergence of linguistics, statistics, and educational technology paves the way for a new class of pedagogical models that are predictive, adaptive, and scalable across learning contexts.

Table 1 : Summary of Traditional Approaches to Error Analysis

Approach	**Strengths**	**Limitations**
Contrastive Analysis Hypothesis (CAH)	Predicts areas where L1 interference may cause errors	Cannot account for developmental or intralingual errors
Error Analysis (EA)	Systematically identifies and classifies learner errors	Descriptive but lacks predictive tools

Interlanguage Theory	Recognizes errors as natural developmental stages	No quantitative modeling; descriptive rather than predictive
Behaviorist Approach	Effective for addressing surface-level phonological errors	Neglects cognitive factors; limited to repetitive drills
Universal Grammar (UG)	Explains commonalities across diverse learner populations	Abstract; lacks practical classroom applications
Cognitive Approach	Explains intralingual errors through rule formation and hypothesis testing	Does not consider external influences like teaching methods

Al-Sadr's Inductive Theory

Sayyid Muhammad Baqir al-Sadr (1977, 1980) proposed the theory of probabilistic induction, which basically combines statistical reasoning with traditional inductive thinking. The idea is simple but important: if something happens repeatedly under similar circumstances, it is more likely to happen again. This is not too different from what Bayesian approaches do today, especially in language learning, where past learner performance can help predict future errors. Induction has been a key part of science for a long time because it helps us generalize from what we observe. Still, as Hume (1748) pointed out, classical induction cannot give us certainty. Al-Sadr tried to fix that by introducing probability into the process, making predictions more reliable, even if not perfect.

In this study, we try to combine Bayesian reasoning with al-Sadr's ideas to look at recurring errors in English learners. Bayesian methods adjust probabilities whenever new data comes in, whereas al-Sadr's induction relies on repeated experience to form expectations (Tenenbaum et al., 2011). By looking at the previous data of the learners, we can get an idea of which errors are likely to happen again. This allows teachers to focus more on common errors while letting less frequent ones be addressed through peer feedback or self-correction. In SLA, thinking of errors as part of a probabilistic system seems useful, because it takes both frequency and context into account when planning instruction.

Al-Sadr's idea of induction is not about strict deduction; it is about reasoning under uncertainty by looking at patterns and try to draw reasonable conclusions, even if you cannot be 100% sure. This works well in SLA because learning is influenced by many factors, by tracking recurring errors, like verb tense mistakes or article misuse, teachers can get a sense of which ones are likely to appear again and decide how to act. This method fits with modern approaches that values data-driven predictions (Goldwater et al., 2009; Griffiths et al., 2008). According to al-Sadr, repeated errors come from both learner habits and systemic features of the learning process. For Teachers, they can classify errors based on how often they happen and where they occur in the lesson by using Bayesian method to help them to estimate the likelihood of these errors, for instance, if a lot of students keep misusing articles even after correction, it is a high-probability error and needs extra instruction. On the other hand, a spelling slip here and there does not need much attention. Adding this predictive angle improves traditional error analysis, which often just describes errors without suggesting action (Erdogan,2005; Khansir, 2012).

Finally, al-Sadr's framework can work well with computational linguistics and machine learning, which use induction to find patterns in large datasets (Ambridge & Lieven, 2011; Goldwater et al., 2009). Bayesian program induction, for example, can infer grammatical rules from limited input. His philosophical ideas offer a guide AI tools for real-time feedback and personalized instruction and by combining philosophical reasoning with practical technology, al-Sadr's theory shows how abstract ideas can actually help improve second language learning today.

Bayesian Formula for Error Prediction

The Bayesian formula is an effective tool for predicting the likelihood of error recurrence in language learning. It uses Al-Sadr's inductive theory and Bayesian probability to estimate the likelihood of an error occurring given previous occurrences. The formula goes as follows:

$$P(\text{Error}|\text{PastOccurrences}) = \frac{P(\text{PastOccurrences}|\text{Error}) \times P(\text{Error})}{P(\text{PastOccurrences})}$$

Each term in this formula plays a crucial role in predicting error recurrence.

1. P(Error| Past Occurrences): Past occurrences of errors can be quantified using the probability of an error recurring, as demonstrated by the term P(Error |Past Occurrences), which provides teachers with a quantifiable measure of the likelihood of a specific error.

2. P(Past Occurrences |Error): Frequency of similar past errors leading to recurrence

3. P(Error): General Likelihood of Error Occurrence, the General Likelihood of Error Occurrence (P(Error)P(\text{Error})P(Error)) is a measure of the likelihood of an error occurring, considering its frequency across all learners and contexts.

4. P(Past Occurrences): The term represents the total frequency of similar historical occurrences in the dataset, acting as a normalization factor to minimize the impact of unusual events.

Bayesian formula proves to be a valuable tool in the context of TEFL, mainly because it helps teachers anticipate where learners might make mistakes and plan accordingly. Basically, it involves looking at past data of the learner like writing samples or speaking tasks and classifying errors into categories such as grammar, vocabulary, or pronunciation. Through investigating how often different errors happen, teachers can estimate which ones are likely to appear again. For example, if most learners keep misusing past tense verbs, it is reasonable to expect this will continue, and extra attention might be needed.

Errors can be grouped into three levels based on how often they occur. High-probability errors, things like verb tense or subject-verb agreement mistakes are common and persistent, so they usually need explicit teaching and repeated practice (Erdogan, 2005 ;Goldwater et al ,2009). While Medium-probability errors, like mistakes with prepositions or word order, happen less often but can still affect communication, errors like these can be handled with exercises that let learners practice in context, and Low-probability errors are rare or unusual, such as misuse of tricky vocabulary or occasional spelling mistakes, and they often don't need intensive teacher intervention. Self-correction or peer feedback is usually enough (Goldwater et al, 2009 ;Zhu, 2019).

This whole approach treats language learning as probabilistic rather than fixed. Learners tend to form expectations from repeated input rather than just memorizing rules (Hsu & Chater, 2010; Goldwater et al., 2009). Bayesian methods let teachers update their expectations about which errors are likely to appear and adjust feedback accordingly. Research in computational linguistics also supports this, showing that probabilistic models—including hierarchical or universal induction algorithms—can predict how learners behave and suggest which areas need focus (Vitányi, 2007; Griffiths et al., 2008; Tenenbaum et al., 2011).

In nutshell, using Bayesian and probabilistic approaches gives teachers a practical, evidence-informed way to prioritize which errors to focus on, tailor instruction to learners' needs, and help improve language outcomes over time.

3. Methodology

This investigation used a mixed-methods quasi-experimental design to develop, test, and evaluate a probabilistic inductive model for predicting and reducing grammatical error frequency in English as a Foreign Language (EFL) in academic writing. The study also examined the relative effectiveness of AI-enabled feedback compared to traditional teacher feedback in addressing high-probability learner errors. The methodology integrates quantitative statistical modeling with qualitative error analysis grounded in Al-Sadr's theory of inductive reasoning, operationalized through Bayesian inference.

Participants

The participants in this study were 100 Iraqi university freshmen (aged 18–22) enrolled in a compulsory academic writing course at a public university. All participants shared Arabic as their first language. Their English proficiency ranged from intermediate to upper-intermediate (B1–B2 level), as determined by the Oxford Placement Test. The students were randomly assigned to two equal groups, Group A (n=50) received AI-assisted feedback while Group B (n=50) received traditional teacher feedback. Participation was voluntary, and informed consent was obtained. All identifying information was anonymized, and ethical approval was granted.

Research Procedure

The research procedure was carried out in three stages:

1. **Pre-Test Writing Task**:
   All students were asked to write a 300–350-word academic essay on a general argumentative topic. This task served as a baseline for identifying each learner's grammatical errors. Five specific grammatical categories were targeted based on their relevance in the literature and their frequency among Arabic-speaking EFL learners and they are verb tenses misuse, word order errors, article omission or misuse, preposition errors and subject-verb agreement errors. Each essay was manually reviewed and coded by using a detailed error classification rubric.

2. **Feedback Intervention**:
   After the pre-test, each group received a different type of feedback, with the first group A (AI-assisted feedback) students uploaded their essays to Grammarly and ChatGPT, receiving instant, AI-generated corrections and metalinguistic explanations, while the second group B (Traditional feedback) instructors provided traditional feedback, highlighting errors and offering brief comments for correction. Students were given one week to revise their drafts based on the feedback received.

3. **Post-Test Writing Task**:
   Students completed a second essay on a new but comparable topic. This allowed the researcher to measure changes in error frequency and type, as well as error recurrence. The same error categories and rating procedures were applied to ensure consistency and comparability.

Data Analysis

Both quantitative and qualitative techniques were used to analyze the data:

- Descriptive Statistics: Frequencies and percentages were calculated to identify the most common grammatical error types before and after intervention.
- Inferential Statistics: A paired-sample t-test was conducted to compare the effectiveness of AI-assisted versus traditional feedback in reducing high-probability errors.
- Bayesian Modeling: To estimate the recurrence probability of each error type, Bayes' theorem was applied using the following formula:

$$P(\text{Error}|\text{PastOccurrences}) = \frac{P(\text{PastOccurrences}|\text{Error}) \times P(\text{Error})}{P(\text{PastOccurrences})}$$

Prior probabilities were derived from pre-test data, and posterior probabilities were compared with actual recurrence rates in the post-test to evaluate the model's predictive accuracy.

- Qualitative Analysis: Selected student samples were examined for patterns of error persistence, correction success, and response to feedback. Qualitative notes were used to supplement quantitative findings and to interpret results in light of Al-Sadr's inductive logic.

Results

This section presents the findings in response to the four research questions guiding the study. The analysis draws on both quantitative data (error frequencies, statistical comparisons, Bayesian modeling) and qualitative observations from student writing samples and feedback behavior.

To address the first research question a comprehensive analysis of the 100 pre-test essays identified 460 grammatical errors distributed across five core categories: verb tense misuse, word order errors, article omission/misuse, preposition misuse, and subject-verb agreement errors. These categories were selected based on their pedagogical relevance and recurrence in prior studies on Arabic-speaking EFL learners. Table 2 summarizes the frequency and prevalence of each error type in the pre-test compositions.

Table 2. Frequency and Distribution of Grammatical Errors in Pre-Test Essays

Error Type	Frequency	Percentage of Total Errors	Percentage of Learners Affected
Verb Tense Misuse	150	30%	40%
Word Order Errors	110	22%	30%
Article Omission/Misuse	75	15%	20%
Preposition Misuse	65	13%	18%
Subject-Verb Agreement	60	12%	15%

The results indicate that verb tense misuse was the most frequent and widespread error, affecting nearly half of the participants. Learners commonly struggled with consistency across tenses and correct auxiliary verb usage. Word order errors often involved misplacement of adjectives, adverbs, and sentence adverbials, reflecting negative transfer from Arabic sentence structure. Article omission, especially the misuse of "the" and "a/an," was observed in noun phrase constructions, aligning with prior findings on L1 influence. These error types were identified as both frequent and persistent across tasks, confirming their instructional priority in EFL writing pedagogy.

The probabilistic inductive model was applied to the pre-test data to calculate predicted recurrence rates using Bayesian inference. These predictions were then compared with observed error frequencies in the post-test, allowing for an assessment of the model's predictive accuracy. Table 3 presents the predicted recurrence probabilities versus the actual post-test frequencies for each error type.

Table 3. Predicted vs. Observed Error Recurrence Rates

Error Type	Bayesian Predicted Recurrence	Observed Post-Test Recurrence
Verb Tense Misuse	56.6%	57%
Word Order Errors	42.9%	43%
Article Omission/Misuse	32.5%	34%
Preposition Misuse	28.0%	29%
Subject-Verb Agreement	22.5%	21%

The minimal deviation between predicted and observed values (±1.5%) supports the high predictive validity of the model. This alignment demonstrates that frequency-based prediction, when modeled through Bayesian inference and contextualized using Al-Sadr's inductive logic, can effectively forecast learner error patterns in academic writing.

To examine the efficacy of different feedback modalities, post-test compositions were analyzed to measure the reduction in high-probability errors for both groups. Group A received AI-assisted feedback (Grammarly and ChatGPT), while Group B received traditional handwritten feedback from instructors. Table 4 outlines the error reduction percentages across both groups.

Table 4. Error Reduction by Feedback Type

Error Type	AI-Assisted Feedback	Traditional Feedback	Difference
Verb Tense Misuse	30%	20%	+10%
Word Order Errors	22%	18%	+4%
Article Omission/Misuse	12%	8%	+4%

A paired-sample t-test revealed a statistically significant advantage for AI-assisted feedback ($t(98) = 4.67$, $p < .01$). In addition to quantitative gains, student reflections collected through brief post-task questionnaires revealed that AI tools offered faster, clearer, and more detailed feedback, contributing to higher learner confidence and self-regulation. Also a paired-sample t-test was conducted to compare the error reduction between pre- and post-tests. Confidence intervals were added to show the precision of the estimated effect.

Table 5. Error Reduction and Effect Sizes by Group

Error Type	Group	t-Value	p-Value	Cohen's d	95% CI for Mean Difference
Verb Tense Misuse	AI Feedback	4.67	< .01	0.72	[6.2, 11.3]

	Traditional	2.89	< .01	0.50	[3.5, 9.1]
Word Order Errors	AI Feedback	3.15	< .01	0.56	[4.1, 8.9]
	Traditional	2.40	< .05	0.44	[2.0, 6.3]
Article Omission/Misuse	AI Feedback	2.85	< .05	0.48	[2.2, 6.7]
	Traditional	1.92	< .05	0.35	[1.1, 4.8]

These results indicate that AI-assisted feedback produced significantly greater reductions in high-probability error types, especially verb tense misuse.

The model applies Bayesian inference to estimate the conditional probability of an error's recurrence, given its previous occurrence and contextual distribution. The general formula used is:

P(Error | Past) = (P(Past | Error) × P(Error)) / P(Past)

For example, if verb tense errors occurred in 40% of learners and had an 85% likelihood of being repeated given prior occurrence, the posterior probability was calculated as follows:

P(Verb Tense | Past) = (0.85 × 0.40) / 0.60 = 0.566 (56.6%)

This estimate (56.6%) corresponded closely with actual recurrence (57%). The same process was applied to each error type, enabling the model to generate individualized error probability profiles for learners. These profiles can guide instructors and intelligent tutoring systems in allocating instructional resources to the most persistent problem areas.

While traditional frameworks such as Error Analysis and Interlanguage Theory provide valuable descriptive insights, they lack the predictive precision and instructional adaptability offered by the Bayesian-inductive model as shown in the comparative summary in Table 6.

Table 6: Comparison of Traditional vs. Bayesian-Inductive Models

Feature	**Traditional Models**	**Bayesian-Inductive Model**
Orientation	Descriptive	Predictive and adaptive
Feedback Strategy	Generalized	Data-driven and targeted
AI Compatibility	Minimal	Fully integrable with NLP systems
Adaptability to Learner Profiles	Limited	High
Instructional Efficiency	Reactive	Proactive

The Bayesian inductive model is grounded in a data-driven approach, which makes it particularly useful for teaching English as a Foreign Language (EFL) with AI tools. Since it relies on probabilities rather than fixed rules, automated systems can offer feedback that is more personalized, focusing on the errors learners are most likely to make.

Based on how errors are classified in the model, teachers can adopt different instructional strategies. High-probability errors, like mistakes with verb tenses, usually need direct teaching, repeated practice, and regular feedback so that learners can gradually overcome persistent challenges. Medium-probability errors often be managed through peer review or guided practice, giving learners the chance to spot and correct mistakes with some support. Low-probability errors, which happen less often, can typically be fixed through independent grammar exercises or semi-automated tasks, allowing learners to take more responsibility for their own learning while still receiving guidance when needed.

Using this probabilistic approach alongside AI tools helps both teachers and technology focus on the errors that matter most. It allows for targeted interventions, better lesson planning, and ongoing monitoring of learner progress. Overall, it offers a practical way to combine personalized learning with scalable instruction, ensuring that support is given where it is most necessary.

Discussion and Conclusion

This study investigated the nature, predictability, and pedagogical treating of errors in academic English as a foreign language (EFL) writing, guided by four research questions. It also explored the differential impact of AI-assisted and traditional corrective feedback within a Bayesian inductive modeling framework based on the inductive inference theory of the chest. Consistent with previous research on Arabic-speaking EFL writers (Bataineh & Batayneh, 2006; Mahmoud, 2011), the data show that verb tense misuse, word order errors, and article omission were the most common and persistent grammatical problems. Verb tense misuse frequently included incorrect use of the simple past or present perfect and omission of auxiliaries. Unorganized sentence structures, including misplaced adjectives and adverbs, also reflected a negative transfer also the misuse of articles, particularly the omission or confusion of "a/an" and "the," resulted from the absence of definite articles in Arabic (Swan & Smith, 2001; Al-Qadi, 2017).

The constancy of these errors across pre- and post-test tasks confirms their stability in interlingual communication development and their pedagogical priority. The Bayesian inductive model effectively predicted error frequencies with high accuracy: deviations between expected and observed frequencies remained below ±1.5% across five error categories. This result suggests that the frequency-based inductive approach, based on Sadr's logic, is well-suited to modern language level analysis applications. It also demonstrates that learners' error histories can form a solid basis for predicting future performance, offering a significant improvement over non-probabilistic descriptive models such as error analysis or interlingual communication theory (Corder, 1967; Selinker, 1972).

AI-mediated feedback proved markedly more effective than traditional teacher feedback in reducing high-probability errors—30% versus 20% for verb tense misuse, 22% versus 18% for word order problems, and 12% versus 8% for article omission. Statistical tests confirmed this difference was statistically significant ($p < 0.01$). These results are consistent with other research emphasizing the importance of immediate, specific, and explanatory feedback via digital tools in enhancing learner self-control and accuracy (Li and Rushan, 2022; Wang et al., 2023). Unlike descriptive models, the Bayesian inductive approach provides quantitative and predictive capabilities for instructional design. Traditional frameworks classify errors after they occur, but they do not guide prioritization or adaptation (Chu, 2019; Khanser, 2012). In contrast, the Bayesian inductive model classifies error types according to probability, enabling teachers or AI systems to dynamically and efficiently allocate focus a critical feature in large-scale or technology-driven language education.

This absolute clear division of grammatical error types into high-, medium-, and low-probability categories enables the adoption of clear, gradual teaching strategies. Regarding high-probability errors, it require extensive training and frequent feedback, while low-probability errors can be addressed through self-correction and peer review. This take us to a result that modern technological perspective integrating the model into AI writing assistants or intelligent tutoring systems which can provide personalized grammatical feedback and adaptive task sequencing based on each learner's probabilistic profile, bridging theory with practice and supporting scalable and adaptive language learning.

Unlike traditional Bayesian theory, which is primarily data-driven and often atheoretical in its epistemology, Sader's inductive reasoning integrates probabilistic reasoning into a structured philosophical framework that justifies the transition from observed regularities to reliable generalizations. His theory utilizes probability theory not only as a computational advantage but also as a necessary condition for rational belief in generalizations, especially under uncertainty. This strengthens the Bayesian model by grounding its predictive logic in a deeper philosophical foundation that explains why replication justifies prediction. On top of that, Sadr's approach emphasizes the ethical and epistemic responsibility of reasoning under uncertainty, a dimension largely absent from cognitive science models, which tend to treat learning as a mechanistic adaptation to the frequency of inputs. Cognitive models in the self-learning approach, such as probabilistic grammatical induction (Goldwater et al., 2009) or Bayesian concept learning (Tenenbaum et al., 2011), focus primarily on mental representations formed by exposures .

On the other hand, Sayyid Muhammad al-Sadr introduce a value-based justification for inductive reasoning that goes beyond empirical considerations. Which suggests a fruitful dialogue between philosophical perspectives and Western cognitive science. While the two converge in their understanding of repetition and prior experience, they differ in their treatment of how and why inductive reasoning is cognitively valid. Incorporating Sadr's logic allows the current study not only to refine the Bayesian model using culture-based logic but also to offer a philosophical counterpoint to prevailing second language acquisition theories that ignore fundamental questions related to the justification of inference. This study proposes a Bayesian inductive model for predicting and reducing grammatical errors in EFL learners' academic writing. Based on Sadr's theory of inductive reasoning, the model applies probabilistic reasoning to learners' error patterns, offering a predictive framework that goes beyond the descriptive scope of traditional second language acquisition theories. Through a quasi-experimental design comparing AI-assisted feedback with traditional feedback across two groups of learners, the study confirmed the model's predictive validity and educational utility.

The findings of this inquiry revealed that verb tense misuse, word order errors, and article omission were the most common and persistent grammatical mistakes. The suggested model was effective in predicting these patterns, with prediction deviations remaining below 1.5% for all categories, while students who received AI-assisted feedback such as Grammarly and ChatGPT showed significantly lower rates of high-probability errors compared to students who received traditional teacher-assisted feedback. This confirms the effectiveness of integrating Natural Language Processing (NLP) tools in EFL writing instruction and highlights the pedagogical value of adaptive feedback based on Bayesian modeling, which is linked to inductive theory and artificial intelligence. Also the comparative analysis demonstrated that the Bayesian inductive model offers clear advantages over traditional frameworks, such as error analysis and linguistic interference theory, by enabling data-driven proactive teaching decisions. Its compatibility with artificial intelligence platforms makes it a strong and promising foundation for intelligent tutoring systems, adaptive writing platforms, and personalized grammar instruction in technology-enhanced language learning environments. The inquiry contributes theoretically by applying a culturally rooted logic system (inductive reasoning) to a modern applied linguistics context, and practically by presenting a scalable model for predictive error analysis in L2 writing.

The results of this investigation open the door for future research to explore the extensions of this model to oral production, reading comprehension, or multilingual learner contexts. Further efforts are needed to improve its integration with AI systems to enable immediate instructional support on a large scale. This imperturbable clarification enhances the model's cultural relevance and pedagogical flexibility in diverse EFL contexts. In conclusion, the Bayesian inductive model bridges theoretical, technological, and pedagogical fields, providing a robust and adaptable framework for enhancing rigor, personalization, and learner autonomy in EFL academic writing instruction.

References

Al-Qadi, M. M. (2017). *English article system errors among Saudi Arabic-speaking undergraduate students: A case of the preparatory year English program learners of King Saud University*. *International Journal of English Language & Translation Studies, 5*(1), 69–77.

Al-Sadr, M. B. (1977). The logical foundations of induction (H. N. al-Sadr, Trans.). Dar Al-Ta'arof

Al-Sadr, M. B. (1980). *Our philosophy*. Islamic Seminary Publications.
Ambridge, B., & Lieven, E. V. M. (2011). *Child language acquisition: Contrasting theoretical approaches*. Cambridge University Press.
Chang, C. W., et al. (2006). The role of prediction error in language learning. *Cognitive Science*, *30*(6), 1061–1086.
Chomsky, N. (1965). *Aspects of the theory of syntax*. MIT Press.
Corder, S. P. (1974). The significance of learner's errors. *International Review of Applied Linguistics, 5*(4), 161–170.
Dulay, H., Burt, M., & Krashen, S. D. (1982). *Language two*. Oxford University Press.
Erdogan, V. (2005). Contribution of error analysis to foreign language teaching. *Mersin University Journal of Education Faculty, 1*(2), 261–270.
Griffiths, T. L., Kemp, C., & Tenenbaum, J. B. (2008). Bayesian models of cognition: Exploring the rationality principle. *Trends in Cognitive Sciences, 12*(7), 287–293.
Goldwater, S., Griffiths, T. L., & Johnson, M. (2009). A Bayesian framework for word segmentation: Exploring the effects of context. *Cognition, 112*(1), 21–54.
Hsu, A. S., & Chater, N. (2010). Probabilistic models for natural language learnability: A simplicity-based approach. *Language Learning, 60*(4), 1–34.
Khansir, A. A. (2012). Error analysis and second language acquisition. *Theory and Practice in Language Studies, 2*(5), 1027–1032.
Krashen, S. (1982). *Principles and practice in second language acquisition*. Oxford University Press.
Kumar, A., et al. (2020). AI-powered writing assistants: A review of current trends and future directions. *Journal of Educational Technology Development and Exchange, 12*(1), 1–20.
Larsen-Freeman, D., & Cameron, L. (2008). *Complex systems and applied linguistics*. Oxford University Press.
Lee, I. (2019). Teacher written corrective feedback: Less is more. *Language Teaching, 52*(4), 524–536.
Parameswari, D. A., Manickam, R., & Je, J. (2024). Error analysis in second language writing: An intervention research. *World Journal of English Language, 14*(3).
Potts, R., & Shanks, D. R. (2019). The benefit of doubt: How and when do prediction errors boost associative learning? *Journal of Experimental Psychology: General, 148*(4), 626-645.
Richards, J. C., & Schmidt, R. W. (1992). *Language and communication*. Longman.
Selinker, L. (1972). Interlanguage. *International Review of Applied Linguistics, 10*(3), 209–231.
Tenenbaum, J. B., Kemp, C., Griffiths, T. L., & Goodman, N. D. (2011). How to grow a mind: Statistics, structure, and abstraction in developmental learning. *Science, 331*(6022), 1279–1285.
Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.
Wu, H.-P., & Garza, E. V. (2014). A study of error analysis in EFL writing. *Journal of Language Teaching and Research, 5*(6), 1256–1262.
Yang, J., Chen, J., & Chang, P. K. (2022). Synthesizing attributes of computer-based

error analysis for ESL/EFL learning: A scoping review. *Sustainability, 14*(15649), 1–16.
Zhang, Z. (2018). Student engagement with computer-generated feedback: A case study. *ELT Journal, 72*(3), 317–328.
Zhu, M. (2019). The important part of error analysis in second language acquisition. In *Proceedings of the 4th International Conference on Humanities Science, Management and Education Technology (HSMET 2019)* (pp. 254–258). Atlantis Press.
Bataineh, R. F., & Bataineh, Z. (2006). *Article omission and misuse among Jordanian EFL writers: Implications for instruction*. *Journal of Educational Research and Studies*.
Chang, F., Dell, G. S., & Bock, K. (2006). Becoming syntactic. *Psychological Review*, *113*(2), 234–272. https://doi.org/10.1037/0033-295X.113.2.234
Corder, S. P. (1967). The significance of learners’ errors. *International Review of Applied Linguistics in Language Teaching*, *5*(4), 161–170.
Ellis, R., Loewen, S., & Erlam, R. (2006). Implicit and explicit corrective feedback and the acquisition of L2 grammar. *Studies in Second Language Acquisition*, *28*(2), 339–368
Goldwater, S., Griffiths, T. L., & Johnson, M. (2009). A Bayesian framework for word segmentation: Exploring the effects of context. *Cognition*, *112*(1), 21–54. https://doi.org/10.1016/j.cognition.2009.03.008
Mahmoud, A. (2011). The role of interlingual and intralingual transfer in English article errors among Kuwaiti learners. In *The Role of Interlingual and Intralingual Transfer in...* (pp. 47–62). *Arab World English Journal*.
Parameswari, D. A., Manickam, R., & Je, J. (in press). Error analysis in second language writing: An intervention research. *World Journal of English Language, 14*(3).
Selinker, L. (1972). *Interlanguage*. IRAL – International Review of Applied Linguistics in Language Teaching, 10(2), 209–231.
Swan, M., & Smith, B. (2001). *Learner English: A teacher’s guide to interference and other problems* (2nd ed.). Cambridge University Press.

Abstract in Arabic

المستخلص
تقترح هذه الدراسة نموذج احتمالي مُعزَّز بالذكاء الاصطناعي للتنبؤ بتكرار الأخطاء النحوية في الكتابة الأكاديمية للغة الإنجليزية بوصفها لغة أجنبية (EFL)، مستوحى من منطق الاستقراء عند السيّد محمد باقر الصدر. يعتمد النموذج على الاستدلال البايزي في تصنيف الأخطاء إلى فئات عالية، متوسطة، ومنخفضة الاحتمالية بالاستناد إلى البيانات السابقة للمتعلمين.
وقد اعتمدت الدراسة تصميماً شبه تجريبي شمل (100) طالب جامعي، جرى من خلاله مقارنة التغذية الراجعة المعزَّزة بالذكاء الاصطناعي (باستخدام ChatGPT وGrammarly) مع التغذية الراجعة التقليدية التي يقدّمها الاستاذ. أُجريت اختبارات قبلية وبعدية على خمسة أنواع من الأخطاء، وأظهر النموذج دقة تنبؤية عالية؛ إذ ظلّت الفروق بين معدلات الأخطاء المتوقعة والواقعية ضمن ±1.5%. كما سجّل المشاركون الذين تلقوا تغذية راجعة معزَّزة بالذكاء الاصطناعي انخفاضاً في الأخطاء عالية الاحتمالية بنسبة 30%، مقارنةً بـ20% فقط لدى من تلقوا تغذية راجعة من المعلّم. وتُظهر هذه النتيجة الفاعلية البيداغوجية وقابلية التوسع للنموذج المقترح.

يُغني منطق الصدر الاستقرائي الإطار البايزي بإضفاء أساس إبستمولوجي مبرهَن للاستدلال الاحتمالي. وبذلك تطوّر هذه الدراسة نموذجاً تعليمياً تكيفياً قائماً على الأدلة، يربط بين النظرية اللغوية والذكاء الاصطناعي ومنهجيات تعليم اللغة الثانية، ويقترح تطبيقات عملية في مجال الكتابة وتعليم القواعد باستخدام الذكاء الاصطناعي ضمن سياقات تعليمية متنوعة.