Enhancing Pedagogical Feedback Quality of Large Language Models via Learning Analytics in a Kanban-Based Platform for Student Self-Regulated Learning Support

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***Abstract*—This study aims to enhance the quality of pedagogical feedback generated by Large Language Models (LLMs) to support student Self-Regulated Learning (SRL), addressing the scalability crisis of human expert feedback. The enhancement focuses on three core functions such as feedback, motivation, and appreciation. A comparative experimental method was employed without fine-tuning, evaluating various Context Engineering schemes enriched with Learning Analytics (LA) on two models: Llama 3.1 8B and Llama 3.3 70B. Evaluation was quantitative (BERTScore, BARTScore, LLM-as-a-Judge) and qualitatively validated by educational psychology experts.**

Results indicate that the effectiveness of the enhancement significantly depends on the model size. The smaller model (8B) achieved the highest performance increase with complex context (ReAct + LA), suggesting a reliance on rich, structured guidance to compensate for its internal limitations. Conversely, the larger model (70B), despite having a superior Baseline performance, showed degraded performance when given overly complex context. The best-performing model (Llama 8B with ReAct + LA) was validated by human experts as "Usable with minor revision". The study concludes that LA-enriched context engineering is an effective, practical, and computationally efficient strategy for improving pedagogical feedback, particularly for smaller LLMs.

***Index Terms*—Large Language Model, Self-Regulated Learning, Learning Analytics, Context Engineering, Pedagogical Feedback**

I. Introduction

The current landscape of higher education demands that s tudents possess the ability to learn independently. However, many are unprepared to face these demands. This creates a serious gap in *Self-Regulated Learning* (SRL) skills, which can hinder learning success and disrupt equitable access to education [1], [2]. This challenge is exacerbated by the digital technologies that characterize modern learning. While offering flexibility, these technologies also present significant distractions and require greater self-discipline [3]. Institutional failure to provide adequate support for SRL development is not merely an academic issue; it is a social issue that impacts students' long-term career prospects and the overall effectiveness of the education system [1].

To address the SRL gap, Zimmerman proposed a framework encompassing the phases of planning (*forethought*), execution (*performance*), and self-reflection (*self-reflection*), wherein SRL is a combination of cognitive, motivational, and behavioral strategies [1], [4]. Individuals with effective self-regulation capabilities are formed through goal setting, strategy planning, active self-monitoring, and thoughtful self-evaluation. A substantial body of research confirms a strong relationship between these skills and academic achievement [1], [2]. However, their development is often hindered by personal, contextual, and social factors, ranging from poor time management and digital distractions to low metacognitive awareness. Metacognition itself refers to the knowledge, awareness, and regulation of one's own thinking, playing a crucial role in building students' awareness of their learning processes [5]. These barriers necessitate structured interventions to guide students through this complex process [3], [6].

The most effective traditional method for developing SRL skills is personalized feedback from human experts. High-quality feedback that focuses not only on the quantity of completed tasks but also on the student's learning process and self-regulation serves as a powerful catalyst for improvement [15, 16] [7], [8]. However, this "gold standard" faces a scalability crisis; increasing student numbers and diverse support needs make the personalized guidance model difficult to implement on a large scale. This is reinforced by studies showing that budgetary pressures drive larger class sizes, thereby severely limiting personal interaction between lecturers and students [9], [10]. This creates an urgent need for innovative technology-based solutions that can complement human expertise.

One such technology is the use of *Large Language Models* (LLMs). LLMs can be employed as virtual tutors capable of providing fast and consistent feedback. LLMs have been utilized in various educational research contexts with diverse breakthroughs. Recent findings show that when LLMs are used for assessment and feedback, *artificial intelligence* (AI) tends to be generous in grading, resulting in scores higher than those given by human experts. Meanwhile, peer and lecturer assessments tend to be lower and more aligned with student performance. AI feedback is often structured but still requires human expert oversight to remain pedagogically relevant, leading to the recommendation of a hybrid approach (combining AI and human experts) [11]. A hybrid approach is recommended as it can combine the speed and scalability of AI with the contextual mastery, empathetic understanding, and pedagogical nuances of human assessment [11]. This recommendation underscores that LLM responses still require expert supervision to be relevant. On the other hand, efforts to standardize AI-tutor evaluation indicate that although current models like GPT-4 are strong in answering questions, they tend to provide answers to students too quickly and lack process guidance. This fact suggests that LLMs are not yet ideal as tutors and cannot yet replace human experts in assessing pedagogical quality [12].

Therefore, this thesis focuses on improving the performance quality of LLM responses as feedback providers to approach the quality of human experts, both quantitatively and qualitatively. This improvement is executed through an evaluation framework that combines human expert references as *ground truth* with quality assessments evaluating relevant pedagogical dimensions [11], [12]. To support this measurement process, this thesis utilizes structured learning process traces. Student learning data, presented in the form of a Kanban board, is used solely as an operational tool to organize and extract process data (card movement, checklists, completion time) that can be mapped to SRL phases (planning-monitoring-reflecting) [13]. The use of the Kanban board serves only as a data enrichment instrument to ensure the evaluation and improvement of LLM feedback quality proceeds more purposefully. In this research, as explained in the subsequent chapter, the focus of novelty lies in the series of evaluations and refinements of the LLM *prompts*. This research aims to improve three main pedagogical functions—feedback, motivational support, and appreciative support—with the practical goal of matching human expert quality on quantitative metrics while simultaneously meeting qualitative quality standards [7], [8], [11], [12]. By comparing LLM outputs with expert specialists, this study assesses the improvement in LLM performance for consideration as a massive yet personalized complementary pedagogical agent for students.

II. Related Works

Woodrow, Koyejo, and Piech [14] address the *Feedback Alignment Challenge*, namely the tendency of LLM-generated feedback to be generic and misaligned with course-specific rigor, terminology, and instructor preferences. They propose *Direct Preference Optimization* (DPO) with teachers in the loop, where TAs select or edit preferred outputs from model pairs during grading, producing preference data that enables fine-tuning without a reward model as in RLHF. Their three-stage pipeline (preference collection, DPO training, inference) forms a self-improving system that increasingly aligns with course expectations across assignments. Using Llama 3.1 8B fine-tuned with HuggingFace DPOTrainer, they conducted controlled blind evaluations with experts and real deployments in large university courses, supported by automated assessment frameworks (e.g., Scarlatos et al. [15]). Results show that DPO outperformed GPT-4o in preference (56.8% vs. 40.2%), insightfulness, correctness, tone positivity, and consistency, though GPT-4o remained stronger in conciseness and suggestions. Deployment demonstrated feasibility at scale and potential for fairness monitoring, positioning DPO as a practical strategy for course-aligned AI feedback generation.

Jacobsen and Weber [16] examine how prompt quality shapes LLM feedback effectiveness in higher education and compare LLM-generated feedback with novice and expert human feedback. They develop a theory-based prompt manual covering role/context specification, mission clarity, instructional logic, and domain specificity, then craft low-, medium-, and high-quality prompts to systematically test prompt effects using ChatGPT-4. Across a geometry learning task involving typical student misconceptions, 60 LLM outputs were coded with pedagogical criteria (e.g., concreteness, activation, empathy, specificity) and compared with feedback written by preservice teachers and experts using the same high-quality prompt. Results show that only high-quality prompts reliably produce strong LLM feedback; LLMs outperform novices in most categories and even exceed experts in explanation, guiding questions, and specificity, while affective dimensions remain mixed. Efficiency gains were substantial, as ChatGPT-4 produced dozens of feedback instances in the time an expert crafted one. The authors highlight the necessity of structured prompt design training for educators and note limitations such as hallucination risks and the need to test student perceptions and transferability across contexts.

Ouyang et al. [17] introduce an RLHF pipeline to align language models with user intent, addressing limitations of large pretrained models that may generate incorrect, unhelpful, or unsafe outputs despite high linguistic proficiency. Their three-stage approach includes supervised fine-tuning on human demonstrations, reward model (RM) training from human comparisons, and policy optimization with PPO using RM predictions as rewards. Drawing on prompts from labelers and real API usage, they train reward models (initialized from GPT-3 6B) and RLHF policies with careful stability controls (KL penalties, learning rate warmup, single-epoch RM training to avoid overfitting). The resulting InstructGPT models show substantial alignment gains: the 1.3B RLHF model is preferred over the much larger GPT-3 175B baseline, while exhibiting improved truthfulness, reduced toxicity, and minimal regression on NLP benchmarks. The study demonstrates that human feedback alignment can outperform mere parameter scaling, while acknowledging remaining errors and offering a blueprint for instruction-following models widely adopted today.

Li and Ma [18] propose CodeRunner Agent, an AI-powered system integrated into Moodle to support self-regulated learning (SRL) in programming education, addressing limitations of external LLM tools that lack course context and produce feedback disconnected from curricula or student behavioral data. The system combines a lecture viewer, CodeRunner execution/grading, and xAPI-based learning analytics to capture rich process data. Its pedagogical foundation is the PPESS model (Planning, Program creation, Error correction, Self-monitoring, Self-reflection), allowing students to request AI help targeted to their current SRL phase. Two context engines drive feedback relevance: LACE (Learning Analytics Context Engine) summarizes engagement and performance patterns from logs, while KCE (Knowledge Context Engine) manages curated course materials, concepts, solution structures, and typical errors. These engines inject SRL and knowledge-context cues into prompts to ensure feedback aligns with curriculum goals while avoiding spoon-feeding. The paper presents a design and planned evaluations—including behavioral analytics and qualitative assessments—to validate impact on SRL, code performance, and pedagogical safety, highlighting the feasibility of an end-to-end, context-aware, LMS-native AI support system.

Strickroth, Kreidenweis, and Götzfried propose a real-time, networked extension of AgileBoard4Teaching to address orchestration challenges in collaborative, task-based classrooms where teachers struggle to monitor diverse group progress simultaneously. Their client-server system includes an authoring mode for task setup, a Kanban interface for students, and a teacher dashboard that displays per-group progress summaries, pending reviews, hand-raise signals, timers, messaging, and live synchronization via WebSockets, with storage handled through Java Servlets and MariaDB. Two evaluations were conducted: a field study with 8th-grade students using a within-subjects comparison of offline versus networked versions, and a simulation study with experienced teachers. Findings show strong preference for the networked system, improved workflow fluency, high usability scores (student SUS 84, teacher SUS 92), and high engagement observed in interaction logs; the simulation study also yielded positive reception despite some bugs. Teachers valued real-time monitoring and ease of scaling boards, suggesting refinements for large-class readability and analytics features. Overall, the study demonstrates the feasibility and pedagogical value of real-time dashboards for classroom orchestration.

In light of the comparative review, this study adopts a pragmatic hybrid approach that prioritizes resource-efficient context alignment, namely high-quality prompt engineering and the injection of learning-analytics signals from Kanban process data, while maintaining strong pedagogical oversight. Instead of relying on costly full-model retraining, the method enriches teacher-authored prompts with contextual features such as task states, time-on-task, and review requests to make LLM feedback more course and SRL aware. Preference-based fine-tuning approaches (e.g., DPO or RLHF) are considered only as long-term options when sufficient preference labels and computational resources are available. Evaluation will combine quantitative comparisons of LLM outputs against expert-based rubrics and automated metrics with qualitative expert judgment to ensure pedagogical soundness. The accompanying real-time dashboard further enables continuous monitoring and iterative refinement of prompts and contextual cues. Altogether, this design aims to deliver a scalable, low-cost pipeline that leverages prompt/context engineering and learning-analytics signals to generate specific, actionable, and pedagogically aligned feedback while keeping instructors firmly in the loop.

III. Methodology

The research was conducted through several stages. The research starting with a comprehensive literature review to understand the current methods for improving LLM performance in producing higher feedback quality. This review covered techniques such as Reinforcement Learning from Human Feedback (RLHF), Direct Preference Optimization (DPO), and Context Engineering, as well as the use of Learning Analytics (LA) to enrich context for LLMs. The literature review also examined the pedagogical aspects of feedback in supporting Self-Regulated Learning (SRL) and the use of Kanban-based platforms for organizing student learning processes. After identifying the research gap, the next step involved selecting various LLM models and prompting techniques for evaluation.

A. Tools

The tools used in this final project consist of both hardware and software as supporting resources. The hardware employed is personally owned. The function of these hardware and software tools is to facilitate code development, chatbot implementation, quantitative and qualitative evaluations, as well as dataset collection. The following is the list of tools used in this research project.

1) **Hardware:**
   - MacBook Pro 14 inch: M1 Pro 10-core processor @ 3.2 GHz
   - Internal GPU: M1 Pro 16-core GPU
   - Neural Engine: 32-core
   - RAM: 16 GB Unified Memory (200 GB/s memory bandwidth)
   - Storage: 1 TB internal Solid State Drive (macOS 26 Tahoe)
2) **Software:**
   - Visual Studio Code version 1.105.1: integrated development environment (IDE) for writing and managing code.
   - Google Docs: tool for drafting questionnaires, performing revisions, and documenting discussion results.
   - Google Sheets: used to visualize and manage Kanban data to share with experts for completion and assessment, facilitating collaboration and metric collection.
   - Anaconda: Python package and virtual environment manager used during development.

B. Units

- Use either SI (MKS) or CGS as primary units. (SI units are encouraged.) English units may be used as secondary units (in parentheses). An exception would be the use of English units as identifiers in trade, such as "3.5-inch disk drive".
- Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.
- Do not mix complete spellings and abbreviations of units: "Wb/m^2" or "webers per square meter", not "$webers/m^2$". Spell out units when they appear in text: ". . . a few henries", not ". . . a few H".
- Use a zero before decimal points: "0.25", not ".25". Use "cm^3", not "cc".)

C. Equations

Number equations consecutively. To make your equations more compact, you may use the solidus (/), the exp function, or appropriate exponents. Italicize Roman symbols for quantities and variables, but not Greek symbols. Use a long dash rather than a hyphen for a minus sign. Punctuate equations with commas or periods when they are part of a sentence, as in:

$$a + b = \gamma \tag{1}$$

Be sure that the symbols in your equation have been defined before or immediately following the equation. Use "(1)", not "Eq. (1)" or "equation (1)", except at the beginning of a sentence: "Equation (1) is . . ."

D. LaTeX-Specific Advice

Please use "soft" (e.g., `\eqref{Eq}`) cross references instead of "hard" references (e.g., `(1)`). That will make it possible to combine sections, add equations, or change the order of figures or citations without having to go through the file line by line.

Please don't use the `{eqnarray}` equation environment. Use `{align}` or `{IEEEeqnarray}` instead. The `{eqnarray}` environment leaves unsightly spaces around relation symbols.

Please note that the `{subequations}` environment in LaTeX will increment the main equation counter even when there are no equation numbers displayed. If you forget that, you might write an article in which the equation numbers skip from (17) to (20), causing the copy editors to wonder if you've discovered a new method of counting.

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Do not use `\nonumber` inside the `{array}` environment. It will not stop equation numbers inside `{array}` (there won't be any anyway) and it might stop a wanted equation number in the surrounding equation.

E. Some Common Mistakes

- The word "data" is plural, not singular.
- The subscript for the permeability of vacuum μ_0, and other common scientific constants, is zero with subscript formatting, not a lowercase letter "o".
- In American English, commas, semicolons, periods, question and exclamation marks are located within quotation marks only when a complete thought or name is cited, such as a title or full quotation. When quotation marks are used, instead of a bold or italic typeface, to highlight a word or phrase, punctuation should appear outside of the quotation marks. A parenthetical phrase or statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.)
- A graph within a graph is an "inset", not an "insert". The word alternatively is preferred to the word "alternately" (unless you really mean something that alternates).
- Do not use the word "essentially" to mean "approximately" or "effectively".
- In your paper title, if the words "that uses" can accurately replace the word "using", capitalize the "u"; if not, keep using lower-cased.
- Be aware of the different meanings of the homophones "affect" and "effect", "complement" and "compliment", "discreet" and "discrete", "principal" and "principle".
- Do not confuse "imply" and "infer".
- The prefix "non" is not a word; it should be joined to the word it modifies, usually without a hyphen.
- There is no period after the "et" in the Latin abbreviation "et al.".
- The abbreviation "i.e." means "that is", and the abbreviation "e.g." means "for example".

An excellent style manual for science writers is [**?**].

F. Authors and Affiliations

The class file is designed for, but not limited to, six authors. A minimum of one author is required for all conference articles. Author names should be listed starting from left to right and then moving down to the next line. This is the author sequence that will be used in future citations and by indexing services. Names should not be listed in columns nor group by affiliation. Please keep your affiliations as succinct as possible (for example, do not differentiate among departments of the same organization).

G. Identify the Headings

Headings, or heads, are organizational devices that guide the reader through your paper. There are two types: component heads and text heads.

Component heads identify the different components of your paper and are not topically subordinate to each other. Examples include Acknowledgments and References and, for these, the correct style to use is “Heading 5”. Use “figure caption” for your Figure captions, and “table head” for your table title. Run-in heads, such as “Abstract”, will require you to apply a style (in this case, italic) in addition to the style provided by the drop down menu to differentiate the head from the text.

Text heads organize the topics on a relational, hierarchical basis. For example, the paper title is the primary text head because all subsequent material relates and elaborates on this one topic. If there are two or more sub-topics, the next level head (uppercase Roman numerals) should be used and, conversely, if there are not at least two sub-topics, then no subheads should be introduced.

H. Figures and Tables

a) Positioning Figures and Tables: Place figures and tables at the top and bottom of columns. Avoid placing them in the middle of columns. Large figures and tables may span across both columns. Figure captions should be below the figures; table heads should appear above the tables. Insert figures and tables after they are cited in the text. Use the abbreviation “Fig. 1”, even at the beginning of a sentence.

TABLE I
TABLE TYPE STYLES

Table Head	**Table Column Head**		
	Table column subhead	***Subhead***	***Subhead***
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[a]Sample of a Table footnote.

Fig. 1. Example of a figure caption.

Figure Labels: Use 8 point Times New Roman for Figure labels. Use words rather than symbols or abbreviations when writing Figure axis labels to avoid confusing the reader. As an example, write the quantity “Magnetization”, or “Magnetization, M”, not just “M”. If including units in the label, present them within parentheses. Do not label axes only with units. In the example, write “Magnetization (A/m)” or “Magnetization $\{A[m(1)]\}$”, not just “A/m”. Do not label axes with a ratio of quantities and units. For example, write “Temperature (K)”, not “Temperature/K”.

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The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks . . .”. Instead, try “R. B. G. thanks. . .”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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Please cite all your references [**?**], [**?**]. References are stored in a bibtex file ”references.bib”. You can use Mendeley or Jabref for your reference manager.

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