Self-service Teacher-facing Learning Analytics Dashboard with Large Language Models

Zuo Wang
The University of Hong Kong
Hong Kong, Hong Kong
u3008567@connect.hku.hk

Weiyue Lin
The University of Hong Kong
Hong Kong, Hong Kong
weiyuelin@connect.hku.hk

Xiao Hu
The University of Arizona
Tucson, USA
xiaohu@arizona.edu

Abstract

With the rise of online learning platforms, the need for effective learning analytics (LA) has become critical for teachers. However, the development of traditional LA dashboards often requires technical expertise and a certain level of data literacy, preventing many teachers from integrating LA dashboards effectively and flexibly into their teaching practice. This paper explores the development of a self-service teacher-facing learning analytics dashboard powered by large language models (LLMs), for improving teaching practices. By leveraging LLMs, the self-service system aims to simplify the implementation of data queries and visualizations, allowing teachers to create personalized LA dashboards using natural languages. This study also investigates the capabilities of LLMs in generating charts for LA dashboards and evaluates the effectiveness of the self-service system through usability tests with 15 teachers. Preliminary findings suggest that LLMs demonstrate high capabilities in generating charts for LA dashboards, and the LLM-powered self-service system can effectively address participating teachers' pedagogical needs for LA. This research contributes to the ongoing research on the intersection of LLMs and education, emphasizing the potential of self-service systems to empower teachers in daily teaching practices.

CCS Concepts

• **Human-centered computing**; • **Visualization**; • **Visualization systems and tools**;

Keywords

learning analytics dashboard, self-service learning analytics, large language models, data visualization

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1 Introduction

The increasing adoption of online learning platforms and the availability of large educational data have led to significant attention on applying learning analytics (LA) to enhance teachers' everyday practices in classrooms [1]. A primary focus of LA research is to support teachers in making well-informed instructional decisions by visualizing students' learning behavior using dashboards [2]. The development of LA dashboards typically involves participatory design engaging teachers in design processes [3]. This collaborative approach ensures that the dashboards are aligned with teachers' pedagogical needs in their teaching practice. Recent initiatives, such as those advocating for human-centered LA and conducting participatory LA workshops, underscore the importance of involving teachers in the design of LA dashboards [2].

However, the design of LA dashboards still faces a "one-size-does-not-fit-all" challenge: Teachers have different requirements for dashboard personalization and complexity influenced by their data literacy levels [1]. The development of LA dashboards requires extensive information technology (IT) expertise and professionals with a deep understanding of educational technology and data analytics, which makes it impractical to expect teachers to create LA dashboards from scratch on their own. This underscores the need for a more flexible and user-friendly solution to ensure that LA dashboards are customizable and accessible for a wide range of teachers. Business intelligence (BI) shares with LA tools the need for data visualization to support effective monitoring and decision-making. In the BI research field, self-service business intelligence (SSBI) is an emerging topic that enables non-technical business departments to access and analyze company data independently, without relying on IT or technical teams [4]. This concept inspires us to apply it in educational scenarios to address the diverse needs of teachers for LA dashboards.

The advent of large language models (LLMs) such as ChatGPT has opened new opportunities for developing self-service systems. LLM-powered systems can comprehend user requirements and generate code at an expert level based on natural language descriptions [5], offering a combination of high customization and self-service through on-demand software generation. This allows non-technical users to utilize LLMs in creating technology products. In this context, we introduce the concept of a Self-Serving Learning Analytics Dashboard (SSLAD) for teachers. SSLAD aims to empower ordinary users with little technological background (i.e. most schoolteachers) to create on-demand LA dashboards with natural languages in a user-friendly interface, enabling them to analyze diverse educational datasets and extract actionable insights. The goal is to reduce the need for extensive technical support and provide more natural interactions when teachers independently create an LA dashboard and interpret large volumes of educational data. In this paper, we propose the design and development of an SSLAD for teachers. A two-part evaluation was conducted to examine the performance

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of LLMs in generating LA dashboards and the effectiveness of the self-service system through usability tests.

2 Background Work

2.1 Teacher-facing Learning Analytics Dashboard Design

Teacher-facing LA dashboards are valuable tools that provide teachers with data-driven insights into student learning and engagement [1]. By integrating data from online learning platforms, these dashboards enable teachers to monitor student progress, identify areas needing improvement, and implement targeted interventions [6]. This functionality facilitates the adaptation of teaching strategies and the refinement of instructional techniques, thereby enhancing the overall effectiveness of the education process [7].

Despite these benefits of teacher-facing dashboards, their integration into daily teaching practice remains limited due to insufficient insight into what teachers want in their classrooms [2]. To ensure these dashboards meet teachers' specific needs, user-centric approaches such as participatory design are increasingly employed in previous research [2, 3]. Involving teachers in the design process allows the development of dashboards to address teachers' specific challenges and be integrated seamlessly into daily teaching practices [3]. This collaborative approach also enhances teachers' sense of ownership and increases the likelihood of adoption [7].

Furthermore, the design of LA dashboards for teachers faces challenges in accommodating teachers' diverse backgrounds, needs, and data literacy levels [1]. To address this challenge, researchers have developed LA dashboards with customization and personalization features [8, 9]. These studies implement domain-specific language (DSL) [8] and rule-based indicators [9] to customize data collection and analysis for teachers. However, the need to explicitly enumerate rules and DSL limits the flexibility, scalability, generalizability, and learnability of these approaches, potentially hindering their effective adoption by teachers.

2.2 Large Language Models (LLMs) for Automated Data Visualization

Nowadays, data visualization is essential for uncovering insights from increasingly generated education data [10]. However, it is challenging to create effective visualizations that enable users to easily understand complex, multidimensional datasets with various attributes and relationships [11]. Recent advancements in natural language processing (NLP) have enabled users to automate the creation of data visualization through natural language input, providing seamless and intuitive experiences for non-expert users [11]. Deep learning has been employed to automatically create data visualizations from human language even before the advent of LLMs such as ChatGPT. Data2Vis is a pioneer work in this area; it trains a neural network on a corpus of visualization specifications to visualize data using Vega[1] [12], a visualization declarative grammar for presenting interactive visualizations in web browsers [13]. LIDA, a recent follow-up to Data2Vis, leverages the patterns learned by LLMs from massive texts and computer programs, requiring no custom models or training data [14].

[1]https://vega.github.io/vega-lite/

Besides generating visuals, data transformation is also essential in the common data visualization process [11]. Text-to-SQL is a research field in NLP that aims to convert users' natural language queries into Structured Query Language (SQL) statements [5]. SQL is a critical domain-specific language designed to manipulate databases and underpins many online education platforms. Similar to data visualization, text-to-SQL research has also evolved from custom model training to leveraging LLMs in zero-shot scenarios where no specific training is required [5]. Existing studies have demonstrated strong capabilities of LLMs such as ChatGPT in text-to-SQL and their significant practical potential [5].

With the advent of LLMs, more advanced tools are being created in the form of chatbots to help automate data visualization [11]. Chatbots are intelligent systems that not only provide visual outputs but also assist inexperienced users in visual analytics with textual feedback, recommendations, and multi-step queries [15]. Although the adoption of chatbots has been favored in many educational contexts [16], there is a lack of study on how chatbots and new LLMs-based visualization techniques can help teachers create LA dashboards on their own and how teachers will interact with such tools.

3 Research Questions

To address existing research gaps in teacher-facing LA dashboard design, this study aims to explore how LLMs can be used to generate visualizations for teacher-facing LA dashboards based on teachers' natural language prompts. Drawing on existing studies of text-to-SQL and automated data visualization, we develop an LLM-powered self-service system that enables teachers to autonomously create LA dashboards and conduct a two-part evaluation to examine its effectiveness. Our research questions are as follows:

RQ1: How can LLMs be effectively utilized to generate teacher-facing LA dashboards with different educational indicators?

RQ2: How do teachers perceive the effectiveness of a self-service system powered by LLMs for creating LA dashboards to address their pedagogical needs?

Our findings contribute to the ongoing research on LLMs and LA dashboards, highlighting the potential of these tools for enhancing teacher engagement and improving educational outcomes.

4 Method

4.1 Student Data Used for Building an SSLAD

To build an SSLAD to answer the above RQs, we collected student data from an online learning platform designed for virtual reality (VR) creation [17] co-designed with students in a previous cohort [18]. The LAVR platform was implemented in a general education course at the University of Hong Kong in the 2022-2023 semester. During the course, students completed two assignments on the platform focused on creating VR stories with their selected themes. Each story is a collection of multimedia elements/objects including images, background music and text annotations. Students reviewed each other's stories through providing comments and ratings.

Specifically, the collected data includes 1) students' information, including [pseudo] names, grades, and years of study, 2) students' VR stories with multimedia elements, 3) students' peer reviews, including comments and ratings, 4) students' behaviour logs (i.e.,

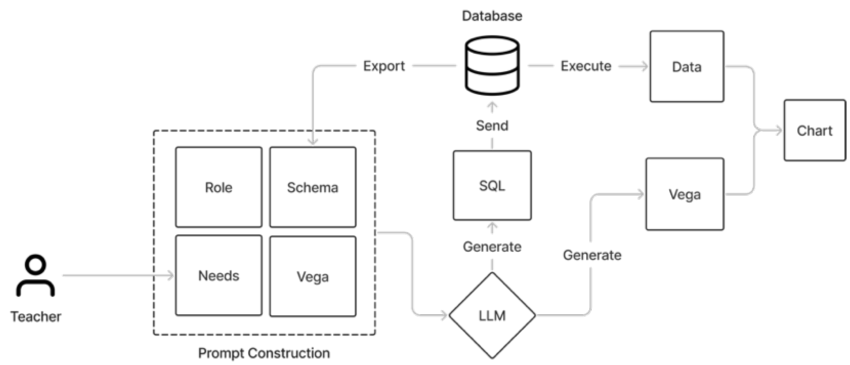

Figure 1: The workflow of chart generation with LLM through prompt engineering

clickstreams) from the platform, including logging in/out, page navigations, various story editing actions, such as updating background music, and adding/removing images/text annotation objects. The data is stored in a PostgreSQL[2] database that powers the learning platform and can be queried using SQL. To safeguard the integrity of the live database, we created an independent snapshot of the live database that included only data for which we had obtained student consent. This approach also ensured that our experiment could proceed without compromising the existing live system. This study has obtained research ethics approval from the University of Hong Kong.

4.2 Prompt Engineering

Prompt engineering is the practice of designing and optimizing input prompts to effectively communicate with LLMs and ensure LLMs generate relevant and accurate responses. To address RQ1, we perform prompt engineering to enable LLMs to generate LA charts on demand using natural language inputs automatically. The complete workflow is illustrated in Figure 1 where prompt engineering plays a crucial role in instructing LLMs to simultaneously generate a SQL query and a Vega specification. The constructed prompt consists of four key components: 1) **Role of the LLM** as a data analyst for teachers, incorporating data from an online learning platform and designing teacher-facing LA dashboards; 2) **Database Schema** automatically export from the database that defines the organization, relationships, and constraints of data within the database (e.g., tables, fields, and data types); 3) **Vega Specification Generation** describes format and instructions for generating Vega specifications for data visualization; and 4) **Teachers' Needs** that include teachers' inquiries and requirements in natural language.

Once the complete prompt is constructed and sent to the LLM, the LLM generates SQL queries for data retrieval and corresponding Vega specifications for visualization. The SQL queries are executed in the database, and the resulting data, along with the Vega specifications, are returned and displayed in a web browser. The effectiveness of this workflow hinges on the LLM's ability to comprehend the database schema, generate valid SQL, and address teachers' needs through accurate Vega specifications. This approach demonstrates a high level of generalizability across online learning platforms in various educational scenarios. Prompt engineering requires no additional training for different datasets. The database schema is automatically integrated into the prompt, enabling easy adaption to other learning platforms with different SQL database designs.

4.3 LLM Evaluation

To evaluate the effectiveness of prompt engineering in LLMs, we developed a set of chart-generation tasks tailored to our classroom data (Table 1). These tasks are based on the indicator groups identified in a previous study [8]. Each task includes a teacher's question that is to be answered by visualization in LA dashboards. Tasks in Table 1 represent a variety of indicators that are often included in teacher-facing LA dashboards and rely on different data sources. The teacher's question in each task captures a unique need from teachers and serves as the input to the LLM which then outputs automatically generated SQL queries and Vega specifications. The validation process in evaluation involves verifying the accuracy of SQL queries and Vega specifications to ensure they align correctly with the corresponding questions.

To gain a comprehensive understanding of LLMs with different capabilities in generating charts, we conducted the evaluation for two latest models from OpenAI: GPT-4o and GPT-4o mini[3]. GPT-4o is recognized as OpenAI's most powerful model, while GPT-4o mini provides a cost-effective alternative with reduced capabilities. By comparing different LLMs' performances, we aim to provide empirical evidence on which LLM is more effective and feasible in generating charts for LA dashboards.

4.4 Self-service System Design

To answer RQ2, we develop an SSLAD system for teachers based on the aforementioned prompt engineering (Section 4.2). The system interface is primarily composed of two sections: the chatbot on the left and the dashboard panel on the right (Figure 2). On the left side is a chat dialog powered by an LLM-based chatbot which is built with our prompt engineering. Unlike the settings in LLM evaluation (Section 4.3), the chatbot allows multiple rounds of conversation, allowing more interactions beyond generating charts. The chatbot can understand teachers' requests and quickly modify the charts. This enables an iterative process similar to previous studies on participatory design of LA dashboards that involve teachers [2].

[2]https://www.postgresql.org/
[3]https://platform.openai.com/docs/models

Table 1: LLM Evaluation Tasks

Task #	Indicator Group	Description	Teacher's Question
Task #1	Learner-related	Information describing the learners	What is the distribution of students by their current academic year?
Task #2	Action-related	Information about actions performed by learners	Who are the top ten students with the highest engagement on the platform?
Task #3	Content-related	Information about contents learners' interacted with or produced	What is the distribution of number of multimedia elements in students' stories?
Task #4	Result-related	Information about outcome of learners' activities	What is the distribution of students' grades?
Task #5	Context-related	Information about the context where learning took place	At what hours of the day do students typically use the platform?
Task #6	Social-related	Information about how learners interact with each other	Who are the top ten students receiving the lowest ratings from their peers?

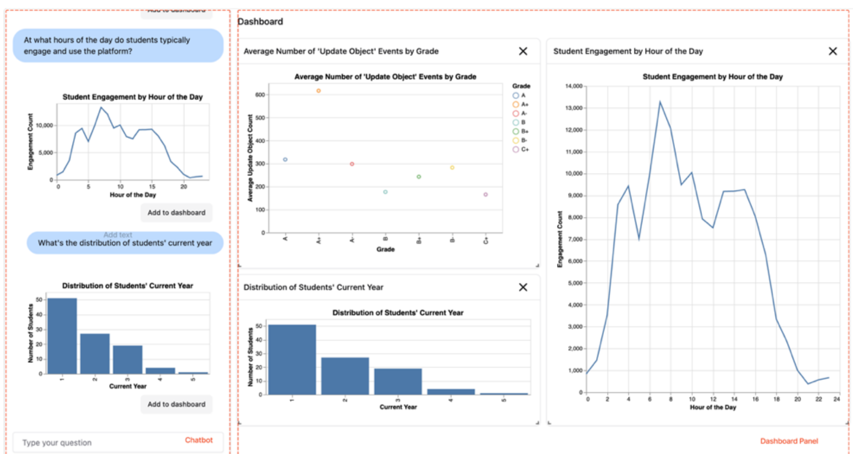

Figure 2: SSLAD interface

For example, teachers can easily convert a generated bar chart into a pie chart by prompting the chatbot with "convert to pie chart". Compared to human participatory design, this approach is significantly faster and more flexible. Additionally, the chatbot can help brainstorm ideas by suggesting which chart to start with. Teachers can also pose follow-up questions about the generated charts, such as inquiries related to data interpretation—an essential component for the successful adoption of LA dashboards [1]. Examples of these chatbot interactions can be found in Figure 3.

Once teachers are satisfied with the charts generated, they can seamlessly add them to the main dashboard panel on the right by clicking the "add to dashboard" button under each generated chart in the chat dialog. The selected chart will then appear in the main dashboard (on the right of Figure 2) and will automatically update in real-time by retrieving the latest data from the database using the generated SQL queries. Additionally, teachers can customize the position and size of each chart within the main dashboard. To further improve the readability, we also generate a title for each chart from LLM. This self-service approach, coupled with a natural and intuitive interface, emphasizes the advantages of empowering teachers in the design process and ensuring that the dashboards meet teachers' specific needs in teaching practice. It is a transformative approach that can enhance teaching effectiveness through autonomous data visualization.

4.5 System Evaluation through Usability Testing

To evaluate the SSLAD system and answer RQ2, we conducted a usability test with 15 teachers. Participants were instructed to interact with the system pretending they were the teacher of the course from which the data were collected. Prior to engaging with the system, participants received an introduction to the course, including the VR creation platform, main assessment task, and student data collected. After being briefed on features and operations of the system, they were required to complete a predefined task: to create a dashboard tailored to their instructional needs. During the usability test session, teachers freely explored the system and interacted with the chatbot in their preferred languages. A think-aloud protocol was employed where teachers verbalized their thoughts, questions, and decisions. The entire session was audio

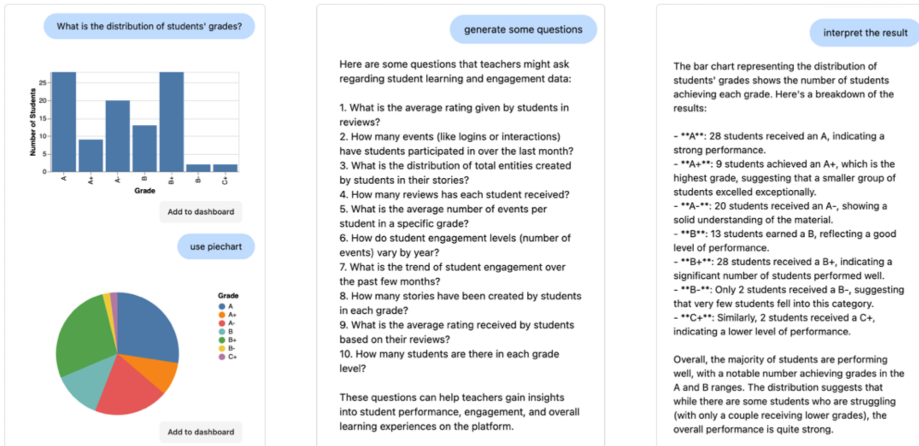

Figure 3: Chatbot interactions on chart revision (left), question suggestion (middle), data interpretation (right)

recorded, transcribed and analysed to gain insights into participating teachers' decision-making processes, challenges faced, and feedback on the system. Each session ended with an exit interview soliciting participants' opinions on how the SSLAD system could benefit their teaching, possible challenges they would face when using this SSLAD in their work, and suggestions for system improvement. Participating teachers also filled out a questionnaire based on usability of e-learning applications [19] and teacher-facing LA dashboards [2, 3]. Questionnaire responses were collected on a 7-point Likert scale, allowing the teachers to rate their levels of agreement with each statement on a scale ranging from 1 (strongly disagree) to 7 (strongly agree).

5 Results and discussion

5.1 Results of LLM Evaluation

We analysed the outputs from two different LLMs (GPT-4o and GPT-4o mini) and both of them successfully generate valid SQL queries and Vega specifications for all tasks listed in Table 1. That demonstrated their effectiveness in retrieving data from the database and displaying error-free charts in the web browser. Although our prompts contain no technique details of SQL and Vega, we benefit from the massive training corpus of LLMs, which contains both SQL and Vega resources and samples.

We further examined the correctness of the generated SQL and Vega specifications in answering the teacher's questions (see Table 1). Notably, GPT-4o made an error in Task #3, producing a SQL query intended to return the number of multimedia elements in stories for each student instead of the distribution of stories by the number of elements. Conversely, GPT-4o mini correctly generated a chart with the x-axis representing the number of multimedia elements and the y-axis showing the number of stories corresponding to each element count. For other tasks, both models generated correct SQL queries and Vega specifications. For Task #1, #4, #5, and #6, both models produced identical SQL queries and Vega specifications. In Task #2, while the generated SQL queries were the same, the different Vega specifications resulted in different charts, as illustrated in Figure 4. GPT-4o mini not only presented the data with a more readable vertical layout but also sorted by the number of engagement counts. Although both models generated SQL queries and retrieved sorted data, GPT-4o mini's Vega specification aligned better with the SQL query results to retain the order of the data.

These tasks represent different needs in teaching and require different indicators for student online learning behaviours. In terms of SQL complexity, Tasks #1, 3, 4 and #5 are similar and only require LLMs to identify a single relevant data source from the database (e.g., current year, grade from students). In contrast, Tasks #2 and #6 are more complicated in that they involve combining multiple data sources (e.g., students and reviews). The correctness of the generated SQL queries highlights LLMs' capabilities in understanding complicated database structures which are commonly found in online learning platforms.

As presented above, both GPT-4o and GPT-4o mini demonstrate high capabilities in our evaluation. Interestingly, the smaller model, GPT-4o mini, outperformed GPT-4o in Tasks #2 and #3, despite GPT-4o being widely regarded as the more capable model. However, the opaque nature of deep learning, particularly in LLMs, makes it hard to explain the performance differences [5]. GPT-4o mini is significantly cheaper than GPT-4o, making it a more cost-effective option for large-scale adoption in educational settings. Our experiment serves as a valuable reference for further integrations of LLMs in generating charts for LA dashboards.

5.2 Results of System Usability Evaluation

Based on the findings in section 5.1, we opted to build the self-service system using GPT-4o mini for performance and cost consideration. We conducted usability tests to evaluate the system with 15 teacher participants who taught a diverse range of subjects, from data science, mathematics, English, geography, to career development. Most (66.67%, n = 10) of the participants have over four years of teaching experience, indicating their solid understanding of educational practices. Their familiarity with LA dashboards varied (M = 4.13, SD = 1.81), which could impact how they perceive the system.

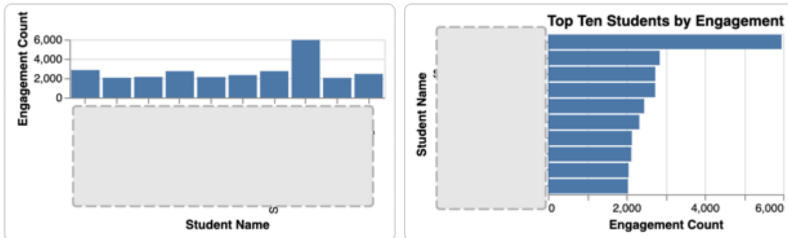

Figure 4: Task #2 results, GPT-4o (left) vs GPT-4o mini (right)

We collected and analysed the questionnaire results, interview data and think-aloud recordings from all participants. According to the results from questionnaires, teachers expressed high satisfaction with the platform (M = 5.67, SD = 0.98) and demonstrated a willingness to integrate similar SSLAD systems into their daily teaching practices (M = 5.67, SD = 1.18). This positive feedback highlights the system's effectiveness in addressing diverse needs of teachers across various contexts. Teachers evaluated system correctness in terms of whether the visualizations met their educational needs, with most participants agreeing that the system could effectively understand teachers' needs (M = 5.47, SD = 0.92) and generate visualization they want (M = 5.60, SD = 1.24). These results suggest that the system outputs align well with teachers' expectations. Regarding ease of use, teachers rated the two primary steps of the system highly: generating charts (M = 5.80, SD = 1.08) and creating dashboards with those charts (M = 6.00, SD = 1.07). On teachers' perceived usefulness, participants reported that the core functions of generating charts (M = 5.53, SD = 1.06) and creating dashboards (M = 5.80, SD = 0.77) were beneficial. Additionally, the three features introduced in the chatbot were also considered valuable: revising charts (M = 5.53, SD = 1.41), suggesting questions (M = 5.80, SD = 0.77), and interpreting data (M = 5.60, SD = 0.83). Furthermore, teachers found the system interface to be easy to understand (M = 5.67, SD = 1.05), convenient to navigate (M = 5.67, SD = 1.11), and focused on essential elements (M = 5.53, SD = 1.13).

While the questionnaire results highlight teachers' positive feedback on the system, the think-aloud recordings and interview data provided deeper insights into their experience with the system through their comments and concerns. The positive feedback was largely attributed to the chatbot's clean design and natural language interaction which effectively reduces teachers' workloads in retrieving and analysing data. The other key benefit was the functions of revising generated charts and creating a personalized dashboard, enhancing the system's overall utility. However, the chatbot also presented a challenge for teachers, as revealed during our interviews. Despite introducing the course context, providing sample prompts, and demonstrating how to use the chatbot to generate questions, many teachers still needed further help during their testing on how to explain their needs to the system. Except for the three teachers (#1, #6, #7) involved in the course where the data were obtained, all other participants required our assistance in using course-specific terminology (such as "story" and "review rating") when interacting with the system. Some participants (#3, #5, #8, #13) suggested that presenting sample questions and predefined charts could help illustrate the system's capabilities to teachers and provide a base chart that they can further revise to meet their needs.

During the testing process, we encountered some system errors when invalid SQL or Vega specifications were generated, although these issues were not found in our LLM evaluations. The whole conversation history, which was sent to the LLM to maintain the context, often led to back-and-forth interactions that could disrupt the context of subsequent questions. This issue was primarily resolved by resetting the conversation to start anew. As conversations lengthened, the cumulative chat history containing various charts and data also impacted the correctness of responses due to context overload, increased complexity, error propagation, and higher computational load on the LLM. The other significant source of incorrect responses was inaccurate prompts due to unfamiliarity with course context. Teachers often needed to revise their prompts through trial and error, sometimes required our assistance. The inaccuracies raised concerns about the system's adoption, as teachers felt the need to verify the responses themselves. This verification process can be challenging and time-consuming, which conflicts with the intent of a self-service system. To address these issues, some teachers (#3, #8) suggested displaying the underlying data alongside the charts and providing data reports when adding visualizations to the dashboard.

6 Conclusion and future work

In this paper, we present a self-service teacher-facing LA dashboard powered by LLMs. Our system allows teachers to independently create LA dashboards, facilitating personalized insights into student learning processes and performance. Through a two-part evaluation, we have demonstrated the effectiveness and potential of this self-service design for teachers, together with challenges encountered by teachers in usability tests. A key technical limitation of the proposed approach is the constraints of Vega grammar, which only supports predefined types of visualizations and thus prevents the implementation of more advanced visualizations, such as network diagrams [1]. Future work will focus on supporting a broader range of visualizations based on existing LA dashboard research. Another limitation stems from the research design, primarily due to the small sample size and controlled lab settings. We aim to integrate the system with popular learning platforms, such as Moodle, and implement it in ongoing classrooms to further evaluate its effectiveness in supporting teachers.

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