

Evaluation of LLM-based Explanations for a Learning Analytics Dashboard

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Abstract

Learning Analytics Dashboards can be a powerful tool to support self-regulated learning in Digital Learning Environments and promote development of meta-cognitive skills, such as reflection. However, their effectiveness can be affected by the interpretability of the data they provide. To assist in the interpretation, we employ a large language model to generate verbal explanations of the data in the dashboard and evaluate it against a standalone dashboard and explanations provided by human teachers in an expert study with university level educators (N=12). We find that the LLM-based explanations of the skill state presented in the dashboard, as well as general recommendations on how to proceed with learning within the course are significantly more favored compared to the other conditions. This indicates that using LLMs for interpretation purposes can enhance the learning experience for learners while maintaining the pedagogical standards approved by teachers.

1 Introduction

With the raise of the demand in education, Digital Learning Environments (DLEs) and particularly Intelligent Tutoring Systems (ITSs) can serve as powerful tools to bridge the gap between demand and supply as well as enrich the overall learning experience Deriyeva et al. [2025]. For example, ITSs have been shown to be efficient to support both self-regulated and teacher-guided learning Kulik and Fletcher [2016]. To promote meta-cognitive skills and support self-regulation of learning processes, many DLEs are using dashboards to show learning analytics on student's ability development and learning behavior to help with reflection on the progress and support decision-making. However, in many cases, additional explanations are needed to make sense of the information presented in a dashboard and act on it appropriately Matcha et al. [2020]. To evaluate perceived effectiveness of such explanations, we conduct a study with human experts (N=12) to evaluate different types of explanations for an Open Learner Model dashboard Bodily et al. [2018] presenting data from a Performance Factors Analysis (PFA) model Pavlik Philip I. et al. [2009]. We find that, on average, teachers tend to favor LLM-based explanations and recommendations over those provided by a human teacher. The data collected as well as the respective prompts and analysis code are available in a git repository ¹.

¹<https://gitlab.ub.uni-bielefeld.de/publications-ag-kml/xlm-explanations-evaluation>

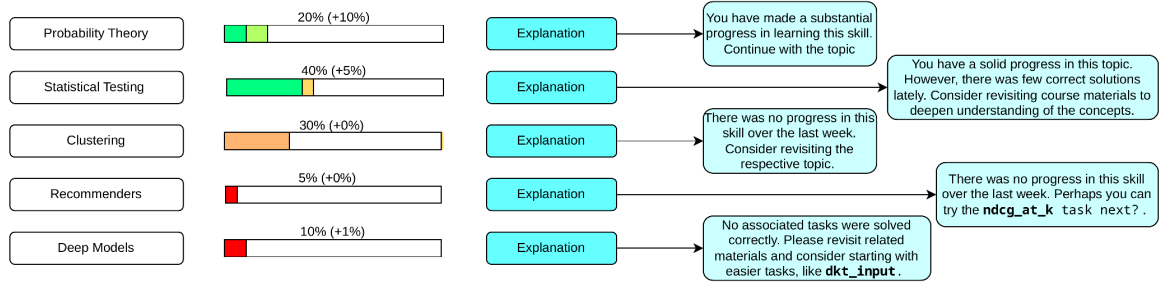


Figure 1: Example of the skill state explanations within the sketch of the dashboard (Condition B).

2 Case Study

To investigate the perceived effectiveness of the explanations of the dashboard, we conducted a within-subject study with $N=12$ participants, where every participant was exposed to 3 conditions in a randomized order: A) a dashboard sketch with no additional explanations, B) a dashboard enriched with explanations and recommendations provided by human teachers (cross-checked by 2 teachers), and C) a dashboard enriched with explanations and recommendations provided by a large language model (Qwen 32B, provided through BIKI interface², prompts can be found in the git repository). For each condition, two simulated example students were presented with different learning performance. After each condition, the participants were asked to evaluate the information they were shown with 3 questionnaires: TOAST Wojton et al. [2020] and two adjusted explanation satisfaction scales Hoffman et al. [2023], one for the explanation of the PFA-based skill states and one for the general course recommendation. Figure 1 shows one of the examples from condition B.

Additionally, the participants were asked to fill in pre- and post-questionnaires to assess their level of experience with teaching as well as strategies they tend to employ to promote the self-regulated learning of the students and to give feedback, as well as to collect their feedback and opinions regarding the study and potential ways to improve the system and explanations they were presented with. The recruited participants were people with university-level teaching experience. The study was approved by the local ethics committee.

3 Results

After the data collection, the questionnaire evaluation results for different conditions were compared against each other with pair-wise t-tests. Firstly, the results of the TOAST evaluation of the three conditions show that there is no little to no difference in the Understanding factor (refers to the understanding of what system needs to do). However, the evaluation of the performance is significantly ($p \ll 0.5$) better for the LLM condition, with Cohen's d of 0.96 compared to the condition with explanations from a human teacher. A similar pattern is reflected in Table 1 showing that LLM-generated explanations to the skill states (right) and recommendations on how to proceed within the course (left) are heavily favored over the two other conditions. While the study is subject to several limitations (sample size, homogeneous population, imperfections in teacher-generated feedback) and the topic would benefit from a more extensive investigation, these results suggest that more extensive and detailed explanations and recommendations generated by LLMs are considered surprisingly effective by

²<https://www.uni-bielefeld.de/einrichtungen/bits/services/kuz/biki/>

	Recommendations		Skill State Explanations	
	Condition B	Condition C	Condition B	Condition C
Condition A	d = -2.4	d = -3.65	d = -0.82	d = -2.20
Condition B	x	d = -0.95	x	d = -1.34

Table 1: Effect size (Cohen’s d) in the pairwise comparison of the evaluation of the conditions. Negative sign indicates preference towards column headers. All the results presented for p « 0.01.

teachers. Hence, in our specific case, we conclude that the LLM can indeed be used to enhance students’ learning experience via automatic explanations of learning analytic dashboards.

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