Edustories: A Collection of Real-world Case Studies from Classroom Practices

Anonymous ACL submission

Abstract

Despite the widely recognized potential of AI in education, most prior work has focused on individualized student assistance. In contrast, the majority of educational practice worldwide still takes place in collective classroom settings. To enable AI research grounded in such practice, we introduce Edustories, a dataset of 1,492 teacher-written case studies describing real elementary and high-school classroom situations involving challenging student behavior, pedagogical interventions, and their outcomes.[1]

Among its applications, Edustories enables systematic evaluation of large language models in providing practicing teachers with feedback on their interventions. Comparing the latest models from four language-model families against standardized expert assessments, we find that current models fall short of human expertise in predicting classroom outcomes; the strongest models reach 58% accuracy compared to 64% of human experts. This gap highlights both the current limitations but also the emerging potential of current AI as assistants for practicing teachers.

1 Introduction

Artificial intelligence has a large potential to support and improve educational practice with over one third of teachers already using AI in their daily practice to prepare materials or personalize exercises (Walton Family Foundation, 2025). Prior work has demonstrated that AI-driven systems can accelerate learning and improve outcomes in a variety of educational domains, including intelligent tutoring systems, automated feedback for programming and mathematics, and adaptive learning platforms (Matos et al., 2025). However, much of this progress has focused on personalized tutoring, where models interact with a single learner and generate personalized explanations, hints, or corrections (Wang et al., 2024a).

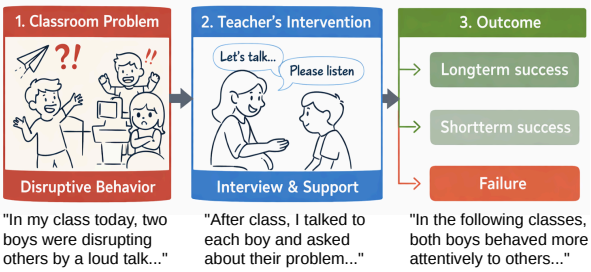

Figure 1: Edustories is a collection of classroom situations, teachers' interventions and their outcomes.

In contrast, collective classroom instruction—in which a teacher simultaneously engages with many students—remains the dominant educational paradigm in elementary and secondary schools. Practicing teachers in such settings face challenges that go beyond individual learning trajectories, including classroom management, social dynamics among students, and the need to balance instructional goals with behavioral interventions (Kearney, 2019). Despite its central role in everyday education, relatively little prior work has aimed to develop automated systems that explicitly support teachers in managing and reflecting on collective lessons (Wang et al., 2024a).

We argue that this gap can be attributed to two main factors. First, collective lessons are inherently more complex than one-on-one educational interactions, as they involve multiple actors, social relationships, and context-dependent dynamics that are difficult to model computationally (Toom and Husu, 2021). Second, the collection of data documenting real classroom situations poses significant challenges: strict ethical and legal requirements for protecting the anonymity of students and practicing teachers limit the availability of detailed, real-world descriptions without compromising authenticity or completeness (Varlamis, 2025). These

[1] The full dataset can be reviewed at https://huggingface.co/datasets/authoranonymous321/Edustories

constraints likely explain why, to best of our knowledge, there exists no other publicly available textual dataset documenting situations arising in collective classroom instruction.

To address this gap and to support the development of AI technologies for assisting teachers in collective lessons, we introduce Edustories, a dataset of 1,492 teacher-authored descriptions of challenging situations encountered during classroom instruction. Each case study includes a narrative description of the situation, the teacher's chosen response or intervention, and the implied outcome, reflecting the teacher's own assessment to what extent the intervention was successful.

Edustories enables a wide range of applications beyond educational AI, including **cognitive science** (e.g., analyzing student diagnoses and hobbies) and **developmental psychology** (e.g., studying how behavior evolves with age). In this work, we focus on one key application in educational AI: **predicting the outcomes of teachers' interventions** to provide actionable feedback. Using Edustories for evaluation, we show that modeling qualitative outcomes of classroom interventions remains challenging even for the strongest LLMs, especially when distinguishing short- vs. long-term success, with 5 of 6 models performing below the lower bound of standardized expert assessment.

1.1 Related collections

Classroom behaviour Several datasets study classroom behaviour using video recordings of teaching practice, including MM-TBA (Huang et al., 2025), TBU (Cai et al., 2025), and FSCB (Lin et al., 2024), with the latter two also providing explicit behaviour labels. These datasets capture what happens in the classroom at an observable level, but they are limited to video data. As a result, they do not represent deeper situational factors captured in Edustories – such as students' prior history, earlier interactions, or how teachers perceive and interpret classroom events. Such information is essential for pedagogical decision-making and providing a meaningful feedback.

Teacher reflections Teacher reflection has been explored through textual datasets aimed at analysing affective and cognitive aspects of teaching practice. The CEReD dataset (Štefánik and Nehyba, 2021) consists of teacher reflection texts annotated for emotional and reflective elements and has been used for emotion classification and reflective analysis (Nehyba and Štefánik, 2022; Zhang et al., 2024), often with the goal of providing feedback to teachers on their practice (Hofmann et al., 2025; Zhang, 2024). However, existing datasets are designed for classification and do not preserve complete classroom narratives. In contrast, Edustories provides holistic case descriptions that retain the rich semantics and narrative of class situations.

Narrative datasets Narrative datasets that model the evolution of situations and the consequences of actors' actions have been developed in several non-educational domains. Examples include datasets focused on moral decision-making and plausibility reasoning (Emelin et al., 2021; Bae et al., 2025), historical narratives (Leteno et al., 2025), social interactions and norms (Forbes et al., 2020), and ethical judgments (Hendrycks et al., 2021a). While these resources share a narrative structure similar to Edustories, they are not directly relevant for educational practice.

2 The Edustories Dataset

Origin and Preparation The case studies contained in the Edustories dataset were written by trainee teachers during their teaching practice at Czech elementary and high schools, coordinated between 2023 and 2026. These trainee teachers are finishing university students completing classroom practice as the last part of their curricula, collecting their case studies with the primary goal of receiving feedback in their collective reflection sessions that follow their teaching practice.

Each case study is recorded in a structured format designed to capture key aspects of classroom situations. Mainly, the collected stories include (1) a narrative description of the situation, (2) an anamnesis providing background information about the student playing a central role in the story, (3) the problem the teacher had to address, (4) the intervention applied by the teacher as a response to the situation, and (5) a description of the perceived outcome of the intervention.

The collected stories underwent a peer-reviewed process where the dataset was further enriched with categorical features including outcome categories reflecting the authors' self-assessment of intervention success: *failure*, *Partial or short-term success*, and *Long-term success*. Other categorical variables provided directly by each story's author include the age of the student, their hobbies, and the presence of any reported disorders or diagnoses.

To make the dataset accessible to the broader AI and NLP research community, the free-text compo-

Feature	Num. filled	Avg. words	Avg. sentences	Num. categories	Most common
Description	1492	141.39	9.41	–	–
Anamnesis	1491	79.55	5.86	–	–
Intervention	1492	134.99	8.21	–	–
category	1475	–	–	15	interview (30.35%)
Outcome	1492	82.78	5.26	–	–
category	1475	–	–	3	long-term success (44.63%)
Student age	1455	–	–	–	12 years
Hobbies	1365	4.75	–	–	computer games (8.17%)
Diagnosis	583	–	–	72	ADHD (22.52%)
Disorders	908	–	–	103	lying (24.66%)

Table 1: Overview of statistics of the main features of Edustories data collection (1,492 samples in total).

nents of Edustories (description, anamnesis, problems, and interventions) were additionally translated from Czech to English. The translation was performed using the service chosen in the expert-based evaluation detailed in Section A.4.

Consent and Anonymization To protect the privacy of all participants, the free-text case descriptions underwent a two-stage anonymization process. First, all personal names and explicit (non-relative) references to dates, times, and locations were automatically identified and randomized using the UFAL Named Entity Recognition service tailored for Czech (Ševčíková et al., 2007). Second, the anonymized texts were manually reviewed during peer-reviewed quality control and augmentation to ensure that no identifying information remains. All authors of Edustories case studies voluntarily provided written informed consent[2] permitting the further use of their data in anonymized form.[3]

3 Experiments: Predicting Success

One of the most direct and impactful applications of AI for improving collective classroom instruction is the provision of feedback to teachers on their instructional and intervention strategies. In the absence of dedicated benchmarks, teachers seeking to benefit from AI-generated feedback must rely on a trial-and-error process, iteratively incorporating suggestions into subsequent classroom practice. This approach has notable limitations: if the quality of the feedback is uncertain, its application may temporarily degrade instructional effectiveness and adversely affect students' learning experiences.

The Edustories dataset provides explicit annotations of intervention outcomes, enabling a systematic evaluation of the quality of AI-generated feedback on teachers' proposed intervention strategies. In this study, we use these outcome annotations to assess the performance of six state-of-the-art language models from five model families, and we compare their predictions to standardized evaluations provided by educational experts.

3.1 Experimental Setup

Data For each case study, we construct evaluation prompts by concatenating the *Description*, *Anamnesis*, and *Intervention* fields. We experiment with five alternative prompt formulations and select the prompt that achieves the highest overall accuracy across models as the final evaluation prompt. We note that differences between prompt variants fall within the evaluation confidence interval (±1.6%), indicating minor sensitivity to prompt choice. Thus, to favour transparency and reproducibility, we use a matching prompt for all models evaluations (detailed in Appendix A.2).

Models We evaluate a set of open-source language models that represent the state of the art across a range of sizes and model families. As a proxy for model quality, we select models that lead their respective size categories on the MMLU-Pro benchmark (Hendrycks et al., 2021b; Wang et al., 2024b). The evaluated models span the most recent models from Llama 3, Qwen 3, Mistral v0.3 and Olmo 3 families (see Appendix A.3 for model IDs).

Expert Annotations As a human reference, we compare model performance against evaluations provided by five educational experts. Our experts are experienced educational practitioners familiar with the Behavior Management Frameworks detailed below. The experts assessed 310 selected case studies from Edustories, evaluating the proposed *Intervention* given the corresponding *Description* and *Anamnesis*. Each intervention was evaluated along three dimensions: (1) **Humanistic orientation** (scale -2 to +2), reflecting emphasis on empathy, dialogue, and student needs versus reinforced control; (2) **Reactivity** (scale -2 to +2), capturing *reactive* (cf. *preventive*) strategies; and (3) **Systematicity** (scale -2 to +2), distinguishing

[2]We reserve the right to withdraw specific samples from Edustories dataset whenever the original author may wish.

[3]The proposal of data collection first underwent review by the ethical committee of the coordinating organisation (to be specified in a non-anonymous version) with a positive result.

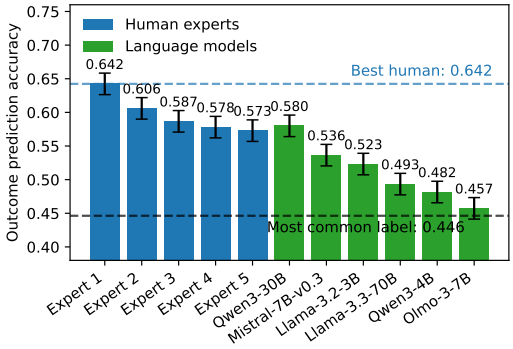

Figure 2: Accuracy of outcome prediction for interventions and case studies of Edustories dataset, for (blue) appropriateness evaluation of human experts and (green) direct prediction of selected language models. Evaluation on n=310 samples to allow comparability with judgements of human experts (§3.1). Confidence interval estimates for $\alpha = 0.1$ covering ±1.6% ranges.

generalizable strategies with contextual adaptation from incident-specific actions.

These dimensions are grounded in Behavior Management Frameworks, namely Social and Emotional Learning (Cipriano et al., 2023), Nonviolent Communication (Batūraitē-Bunka et al., 2024), Positive Behavioral Interventions and Supports (Bradshaw et al., 2012), and Restorative Practices (Fronius et al., 2019). Based on these aspects, experts finally rated the overall **Appropriateness** of each intervention on a scale from -2 to +2.

To align expert judgments with the Edustories outcome labels, we map Appropriateness scores to outcome categories as follows: a score of -2 correspond to *failure*, a scores of -1 and 0 corresponds to *partial or short-term success*, and scores of +1 and +2 correspond to *long-term success*.

3.2 Results

Figure 2 compares outcome prediction accuracy between human experts and selected language models. Among all evaluated models, only one model (Qwen-3-30B) reaches performance overlapping with human expert accuracy, achieving 0.580 compared to 0.573–0.587 for the lower-performing experts. Qwen-3-30B also exhibits a clear margin over all other language models.

Our results indicate that model size is not a decisive performance factor; For example, the larger Llama-3.3-70B underperforms the smaller Llama-3.2-3B, suggesting that architectural choices, training data and other training refinements play a more important role than scale alone. This has positive implications for practical deployment. We hypothesise that outcome prediction may depend more on general reasoning capability, as the two best-performing models also show particularly strong performance on reasoning-focused tasks.

Comparative analysis A closer comparison of the best-performing model and human expert (Appendix A.1) reveals qualitatively different error patterns. Human experts' errors predominantly arise from assigning failure cases to short-term success, while they remain highly accurate (84.41%) in identifying long-term success. In contrast, Qwen-3-30B and other language models primarily struggle to distinguish between short- and long-term success.

This pattern is consistent across experts, who substantially outperform language models in identifying long-term success (71.97% vs. 49.88%), though they are more susceptible to other types of errors. Overall, performance variance is considerably higher among language models (0.457–0.580) than among human experts (0.573–0.642).

Taken together, these results indicate that human experts remain more reliable and consistent, despite the near-expert performance achieved by the best-performing language model. Nevertheless, the complementary nature of errors made by humans and models suggests that current language models may already provide value as assistive tools rather than replacements for educational experts.

4 Conclusions

We introduce Edustories, a new collection of 1,492 authentic, teacher-written case studies from elementary and high-school classrooms. The dataset was proofread and anonymized through a two-stage process that included human review, making it the first available educational dataset documenting classroom practices at this level of detail.

Edustories enables a wide range of research directions in education, linguistics, and AI, including sentiment analyses, identification of predictive features of successful interventions, and evaluation of AI assistants in collective educational practice. In this work, we focus on one such direction: assessing the ability of current LLMs in providing feedback on teachers' proposed interventions.

Our results show that while the best-performing models can reach the lower bound of human expert performance, language models remain less consistent and exhibit different failure modes than humans. These findings highlight the importance of specialized educational benchmarks before using AI assistants in practice, but also underscore their existing potential for educational practice.

Limitations

We acknowledge several limitations of our work that point to directions for future research. First, our evaluation of outcome prediction does not fully capture the complexity of real-world deployment of assistive AI in educational settings. While we focus on outcome prediction as a key indicator of practical viability, effective integration into practice would likely require a more sophisticated pipeline, supporting teacher-facing feedback, such as free-form rationales or conversational interfaces. Although this lies beyond the scope of our current contribution, we view it as an impactful and interesting direction for future work at the intersection of AI and human–computer interaction.

Second, we acknowledge the limitation of Edustories dataset in the quality of English translation of free-form texts, constrained by the precision of the commercial translation services. While we pick the translation service for free-form texts systematically based on human assessment from among Google Translate, DeepL and Open-source Czech-English translation models, we note that errors may occus and estimate that 5–10% of stories may contain a type or "translationese" text. However, as we do not dispose of sufficient power of human proofreaders to manually verify all the English versions of our stories, we will appreciate the effort of the community in helping us to identify cases where the quality of free-form features of Edustories could be improved and possibly helping us to address them.

Finally, we acknowledge the limitation of the scope our evaluated models, that do not include the models over 100-billion parameters due to our computational restraints. Note that we intentionally exclude the proprietary API AI services from evaluations as these may not present an apples-to-apples comparison to raw language models evaluated locally. Furthermore, we believe that controlled, locally-deployable models correspond better with the practical application of feedback delivery systems as these systems will operate directly with sensitive data from classrooms that may not be safely shared with third parties.

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A Experimental details

A.1 Confusion matrices

Tables 2 and 3 shows classification confusion matrix for the best-performing human annotator and

	Predicted outcome		
True outcome	**fail**	**success-short**	**success-long**
fail	0.00	91.67	8.33
success-short	7.69	27.88	64.42
success-long	2.69	12.90	84.41

Table 2: **Best expert:** Row-normalized confusion matrix (%) for three-way outcome classification for the best-performing human expert.

	Predicted outcome		
True outcome	**fail**	**success-short**	**success-long**
fail	41.67	8.33	50.00
success-short	12.62	41.75	45.63
success-long	7.57	24.32	68.11

Table 3: **Best language model:** Row-normalized confusion matrix (%) for three-way outcome classification for the best-performing **language model** (Qwen3-30B).

	Predicted outcome		
True outcome	**fail**	**success-short**	**success-long**
fail	31.67	55.00	13.33
success-short	17.49	28.95	53.56
success-long	5.87	22.16	71.97

Table 4: **All experts:** Row-normalized confusion matrix (%) averaged across all human experts for three-way outcome classification.

	Predicted outcome		
True outcome	**fail**	**success-short**	**success-long**
fail	45.83	45.83	8.33
success-short	14.06	54.51	31.44
success-long	8.29	41.83	49.88

Table 5: **All language models:** Row-normalized confusion matrix (%) averaged across all language models for three-way outcome classification.

best-performing language model, respectively. Tables 4 and 5 shows classification confusion matrix aggregated over all human experts, and evaluated language models, respectively.

A.2 Evaluation Prompt

Table 6 displays the exact form of the best-performing prompt we applied in our evaluations. The selection process is detailed in Section 3.1.

Prompt
You will be given a short case study written by a teacher.
It describes a situation and the intervention chosen.

Your task is to classify the expected overall outcome of
the solution into exactly one category:
'Longterm success', 'Partial success', 'failure' or 'I don't know'

Important rules:
- Choose exactly one category.
- Reply with the category name ONLY, copied exactly.
- No punctuation, explanation, or extra text.

Case study:

"""{Description} {Anamnesis} {Intervention}"""

Response
One of {'Longterm success' / 'Partial success'/ 'failure' / 'I don't know'}

Table 6: Final prompt we use in our evaluations. Chosen as the best-performing variant among 5 candidates.

A.3 Evaluated models

In our experiments, we specifically evaluate the following models with HuggingFace identifiers: Qwen3-30B and Qwen3-4B introduced by Yang et al. (2025) corresponding to *Qwen3-30B-A3B-Instruct-2507* and *Qwen3-4B-Instruct-2507*, Llama 3.2-70B and Llama 3.3-3B introduced by (Grattafiori et al., 2024) corresponding to *meta-Llama-3.3-70B-Instruct* and *Llama-3.2-3B-Instruct*, Mistral-7B introduced by Jiang et al. (2023) corresponding to *Mistral-7B-Instruct-v0.3* and Olmo-3 introduced by Olmo et al. (2025) corresponding to *Olmo-3-7B-Instruct*.

A.4 Translation process

To make Edustories accessible to a wider scientific community, we additionally translated the anonymised free-text features from Czech to English. We experimented with four translation tools available to date[4]: (1) Open-source Opus translation models (Tiedemann and Thottingal, 2020), Google Translate API[5], DeepL[6] and GPT 5.2 Thinking[7]. For a randomly-chosen set of 50 samples from our datasets, we manually verified the fluency and semantic equivalence to the source texts. We found that the GPT 5.2 API performs on par with DeepL in terms of semantic equivalence – in 50 samples, annotators identified 2 cases where the semantic equivalence was not perfect but with minor mistakes. However, we found that the GPT

[4] As of November, 2025
[5] https://translate.google.com
[6] https://deepl.com/en/translator
[7] https://chatgpt.com/

5.2 outperforms other services in fluency, where our annotators did not identify any mistakes among the 50 samples. Based on this evaluation, all translations provided in Edustories were produced by GPT 5.2. Note that the original features (in Czech) are retained in the collection and can be used for refinements with future translation models or as a source of translation to other languages.

B Use of AI Assistants

We acknowledge the use of AI assistants during the creation of this paper, namely in plots refinements, tables formatting, grammar control and text polishing. AI assistants were not employed in the creation of ideas, results and connections described in this paper.