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Development of a machine-learning-driven digital teaching assistant that utilises student engagement data to improve access to and success in K-12 STEM education

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Student engagement is a key predictor of academic achievement and is closely linked to career awareness, interest, and preparedness. Measuring student engagement during STEM learning is challenging for teachers, given the dynamic and ever-changing nature of these learning environments. Even when engagement data can be collected, leveraging this information to refine and personalise instruction requires significant experience and time. To address this, we are developing Scoutlier EngagEd, a digital teaching assistant that embeds in existing Learning Management Systems (LMS) to automatically and invisibly gather multidimensional data on student engagement and performance during STEM learning. These data are being leveraged to model student learning and generate insights that produce human-like, actionable recommendations through a Large Language Model (LLM) for teachers to improve STEM learning outcomes.

Keywords: experiential learning, LLM, machine learning, models of learning, multidimensional data capture, student engagement, STEM

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Introduction

The landscape of K-12 education, particularly in STEM, has been drastically altered globally by the COVID-19 pandemic (Delen & Yuksel, 2023). We face a critical juncture with profound learning loss (NAEP, 2022), a shortage of STEM educators (Darner & Boesdorfer, 2022), and increased equity gaps, as students of colour, those in low-income households, and rural communities remain less able to access key instructional resources (Raugust & Berkman, 2022).

The surge in technology investments made by schools in response to the pandemic presents an important opportunity for innovative solutions that augment limited human and institutional resources and transform the delivery of STEM education (Raugust & Berkman, 2022).

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Particular focus is being directed towards hands-on and experiential STEM learning that connects with real-world experiences and careers. Student engagement consistently emerges as a key predictor of positive academic outcomes (Fredericks et al., 2004; Lei et al., 2018; Sinatra et al., 2015), and there is a growing literature that STEM learning activities can be more engaging and impactful than traditional curricula because they attend to students' interests and personal values (Means & Stephens, 2021).

A critical limitation of current STEM instruction is that it does not evaluate or adapt to student engagement during the learning process (Rodriguez, 2015). Manual approaches (e.g. teacher observation) to track and interpret student engagement in STEM learning environments have not proven effective or sustainable, especially for less experienced teachers (Harris & Sass, 2011; King Rice, 2010), and few digital systems have been developed and optimised for this dynamic learning setting.

Traditional descriptive analytics, while informative, are limited in their ability to guide educators on how to adapt their instructional strategies effectively. By evolving from descriptive insights to prescriptive recommendations, we can equip teachers with the tools they need to personalise learning and respond dynamically to student needs. AI, particularly generative models, offers a transformative approach to addressing this challenge. Generative models, such as Large Language Models (LLMs), can synthesise complex engagement patterns and produce actionable insights with tailored recommendations that help teachers make real-time adjustments to their instruction.

Here we report on our current research that explores Scoutlier EngagED, a novel digital data collection and analysis teaching assistant. Scoutlier EngagED leverages machine learning and AI to provide STEM teachers with real-time insight into student engagement and intuitive recommendations on how to enhance their students' performance and growth.

Methods

Development of Scoutlier EngagED

Current digital learning platforms and learning management systems (LMS) are used to collect student learning data and support machine learning strategies. These tools identify and classify student engagement in virtual and classroom learning (Dewan et al, 2019), predict grade or dropout likelihood (Gray & Perkins, 2019), and create early warning indicator systems (Flanagan et al, 2022). Some of the most promising models apply neural temporal point processes (TPPs, Shchur et al., 2021) and related generative probabilistic techniques to identify and group students around latent learning intents. A burgeoning literature supports the integration of text identified by LLMs to not only augment the interpretability of computer-generated data but also to achieve broader transformation of education (Bailey, 2023).

However, STEM learning presents a unique set of challenges to the measurement, modelling and application of student engagement using digital systems, especially related to:

- Data collection. How can we collect varied and multi-modal student data in dynamic and ever-changing STEM learning settings in a way that is unbiased and does not impact the learning process?
- Data modelling: How can we develop models that process diverse multi-modal data types, establish student learning trajectories, and identify meaningful trends?
- Insight generation: How can we generate recommendations that improve engagement and adapt to diverse educational objectives and desired learning outcomes?

To address this, we have developed Scoutlier EngagED, a digital STEM teaching assistant that embeds within existing classroom technology and software (Figure 1). It supports the design and delivery of scaffolded STEM lessons, self-paced learning, and multi-modes of student response (e.g. text, image, video, numerical). Key to this tool is its ability to collect data on student interactions that are predicted to serve as indicators of student engagement (Sinatra et al., 2015, Table 1), and use these insights to inform adaptations to optimise learning outcomes.

Figure 1. Framework and capabilities of Scoutlier EngagED digital STEM teaching assistant.

Collection of student engagement data by Scoutlier EngagED during experiential learning

As a student progresses through a STEM lesson the Scoutlier EngagED digital teaching assistant captures over 20 different types of student interactions or 100+ indicators of student engagement per lesson. A selection of these indicators is reported in real-time to teachers through an 'Engagement Report' dashboard (Figure 2) to support formative assessment, as well as design and adaptation of instruction.

Table 1. Engagement types mapped to student interactions captured on the Scoutlier EngagED digital teaching assistant.

Engagement type	Definition	Examples of student interactions on Scoutlier EngagED that inform engagement type
Behavioural	Positive conduct and involvement in academic tasks	Time spent on individual learning tasks and the lesson overall Percent of lessons completed
Cognitive	Investment in learning through efforts to understand, using flexible problem solving, choice of challenging tasks	Length and complexity of written, oral, and video responses Learning supports accessed Choice of response mode selected (e.g. text vs. spoken vs. video)
Emotional	Emotional reaction to academic subject area	Student self-reported interest in and preparedness for the corresponding lesson
Agentic	Exertion of learning agency by enriching, personalising, modifying, or requesting instruction	Views of collaborative work products Choice of tasks

Note: Engagement type and their definitions are from Sinatra et al. (2015).

Figure 2. Engagement Report showing selected student engagement data collected by Scoutlier EngagED.

Engagement Report

Performance Overview

	STUDENT PERFORMANCE	CLASS AVERAGE
Last Date Worked On	February 27, 2024	
Percent Complete	90%	81%
Time Spent on Lesson	69m 46s	75m 20s
Grade	90/100	88/100
Comment	Great work.	NA

Task Overview

Task (1) Going Places: Using children's literature to inspire creativity	Task (2) If you chose "Light it Up", complete the following steps.	Task (3) If you chose "Make it Move", complete the following steps
	STUDENT PERFORMANCE	CLASS AVERAGE
Accessed (1) Going Places read along	✗	76%
Step (1) Watch the video, or listen the read aloud		
Completed	✓	100%
Time Spent on Step	0m 44s	12m 13s
Reviewed Peer Responses	✗	NA
Paragraph Length	136 Character	23 Character
Step (2) What is one positive and one negative u		
Completed	✓	100%
Time Spent on Step	6m 56s	3m 45s

Note: Scoutlier EngagED generates an engagement report for each student that automatically displays key lesson-level and task/step-level data that includes time spent, % lesson completed, and whether or not the student collaborated with peers or viewed supporting instructional materials.

Creation of a student engagement data set for research

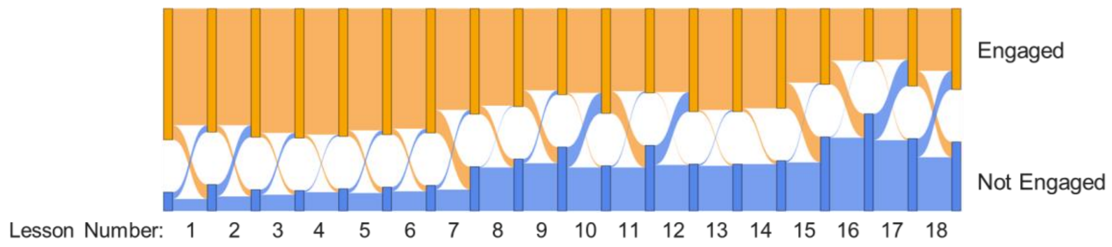
Through an exploratory NSF iTEST program (DRL-2148451) we have created an 18-lesson data science, machine learning, and AI curriculum for high school students that was delivered with the support of our Scoutlier EngagED digital teaching assistant. The curriculum was designed to make these emerging technical fields more accessible and engaging for students with varying levels of academic preparation. Between January 2023 and June 2024, we collected over 300,000 engagement data points from approximately 175 students at six public schools and one private school in mostly urban communities in Rhode Island as they worked through this curriculum. The selected schools represent diverse learning populations and settings: including varied numbers of students per class (from around 4 to over 25), age range and gender of students (including an all-girls school), preparation and motivation of students to participate in the curriculum (from students in a computer science program with extensive coding experience to students obliged to take the course and with limited math or coding preparation), and the instruction type and philosophy of the school (from traditional public schools to schools with exploratory learning and assessment approaches). Using Institutional Review Board (IRB)-approved protocols, subsets of student data were de-identified and used for analysis.

Results

Trends in cohort and classroom-level engagement data

Our initial exploration of student engagement data captured by the Scoutlier EngagED digital teaching assistant focused on macro trends at the cohort and classroom level within our STEM curriculum. By tracking well-established engagement metrics, including work initiation, time-on-task, and rate of completion of lessons, we identified clear patterns in engagement. Considering the frequency of students who initiated work within each lesson, we were able to identify a trend of gradual disengagement over the course of the curriculum and discover areas of the curriculum with large changes in engagement (Figure 3, and data not shown).

Figure 3. Flow of student engagement during an 18-lesson high school data science, machine learning and AI curriculum.

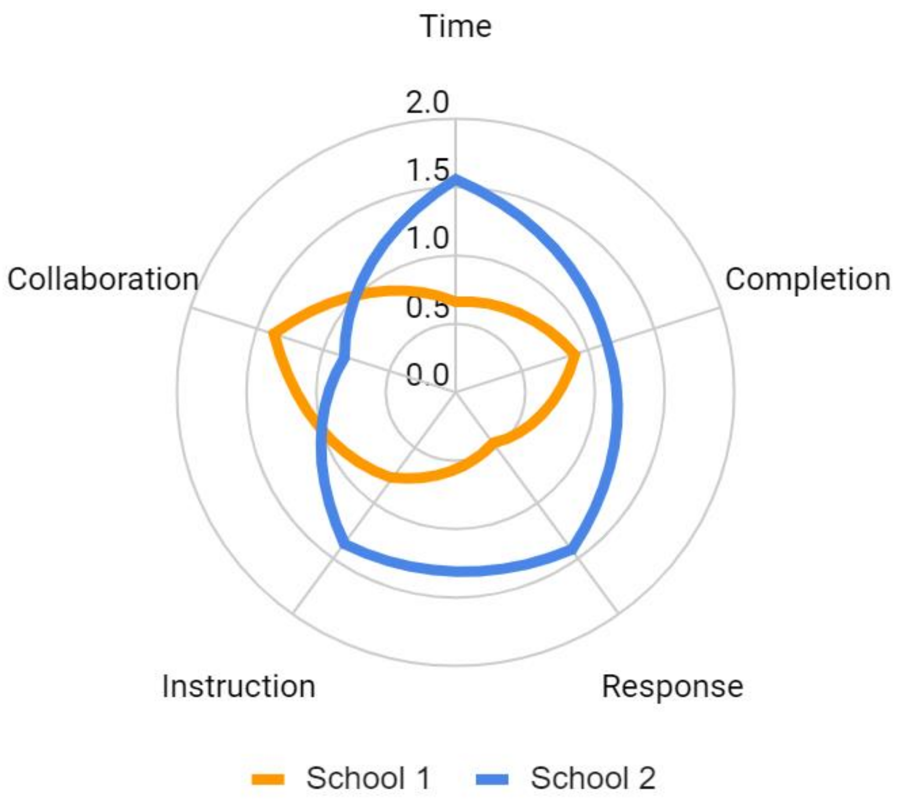


Legend:

Orange bars:	Engaged	Orange connectors:	Decreased engagement
Blue bars:	Not engaged	Blue connectors:	Increased engagement

To determine whether we could also use Scoutlier EngagED to track more granular measures of engagement we determined the average length of written student response (response), the rate at which students accessed instructional materials provided (instruction), and the frequency with which they viewed each other's responses and comments (collaboration), in addition to average time-on-task (time), and completion rate (completion). All these metrics were indexed against the average for all seven participating schools (average over all schools = engagement score of 1) (Figure 4). Our results suggest meaningful differences in the student engagement profiles between schools. For example, comparing School 1 and School 2 for lesson 6, students in School 1 scored below average on all measured indicators except for collaboration, while those in School 2 scored above average except on this indicator (Figure 4).

Figure 4. Different student engagement profiles emerge at the whole class level.



Legend:

Time: Average time-on-task

Completion: Completion rate

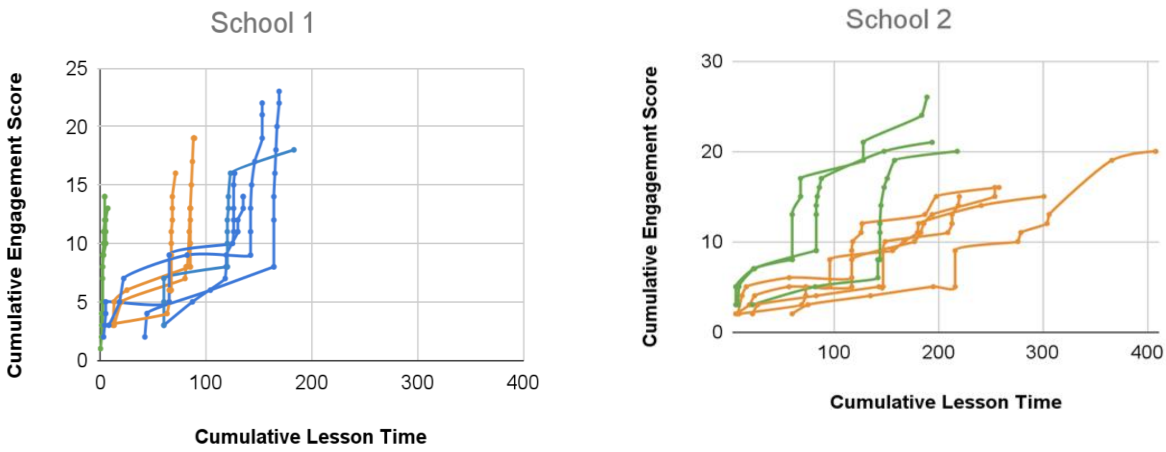
Response: Average length of student written responses

Instruction: Rate at which students accessed instructional materials provided

Collaboration: Rate at which students viewed each other's responses

To explore whether the engagement profiles reflected differences in individual students' engagement behaviours, we established simple learning engagement trajectories for each student. These documented the number of engagement interactions (response, instruction, and collaboration, as defined in Figure 4) registered on the Scoutlier EngagED digital teaching assistant as students progressed through a lesson. As shown in Figure 5, students appear to cluster around distinct learning trajectories that are differentiated both in their time scale and in level/rate of engagement. Additionally, students in different classrooms appear to exhibit different learning trajectories. Individual students' (School 1, n = 12; School 2, n = 8) learning trajectories were established for lesson 6 by calculating the cumulative time spent learning by summing time spent on each individual learning task and step (total of 4 tasks and 12 total learning steps). A cumulative engagement score was calculated by adding the number of engagement interactions measured (e.g. response, instruction, collaboration) at each step.

Figure 5. Students cluster around learning trajectories defined by engagement indicators that differ between classrooms.



Legend: Line colour identifies students who belong to the same cluster.

Applying machine learning and AI to provide deeper, actionable insight into student engagement

To determine the potential of machine learning and AI for creating prescriptive, interpretable, and actionable insights, we integrated traditional unsupervised machine learning techniques with generative AI models to analyse the student engagement data collected by Scoutlier EngagED. Specifically, we applied KMeans clustering (Lloyd, 1957; Liu, 2022; Tuyishimire et al., 2022) to identify groups of students exhibiting similar engagement levels based on metrics such as time spent on lessons, percentage of lesson completion, and grades. This clustering analysis revealed seven distinct student engagement profiles throughout the course (see Table 2). The cluster representations (centroids) were passed through GPT-4 (Achiam et al., 2023), to translate these cluster centres into recognisable engagement profiles. The LLM provided distinct profile titles such as 'Disengaged', 'Inconsistent Strugglers', 'Selectively Engaged', and 'High Achievers', as well as explanations and targeted educational strategies for each group (see Table 2 for full outputs). Although the initial cluster profiles and educational recommendations are relatively general, they do align with broad themes uncovered through qualitative research with the same teacher and student cohorts (data not shown). We are currently collecting additional user feedback to validate and fine-tune our LLM outputs, and—ultimately—apply reinforcement learning from human feedback (RLHF) to align with the unique requirements of STEM teachers.

Table 2. Scoutlier EngagED LLM output describing engagement cluster features and recommendations.

A: LLM translation of cluster representations into engagement profiles

Cluster	Title	Profile	Characteristics
A	The Moderates	Likely to be average performers who may need motivation or help to improve their understanding and potentially boost their performance.	Moderate engagement and time spent with somewhat high completion rates and average grades. This group might be putting in just enough effort to get by but not excelling.
B	The High Achievers	These are the consistent top performers who are likely very motivated and possibly benefit from strong study habits or a good grasp of the material.	These students show high time investment, complete engagement, full completion rates, and top grades. They excel across all aspects of their coursework.
C	Selectively Engaged	Students who perform well but might not find the lessons consistently engaging. They could benefit from more challenging materials or tasks that stimulate their interest and engagement more deeply.	Despite lower engagement levels, these students manage to complete their work and achieve perfect grades when they do engage. This suggests they may be under-challenged or not consistently motivated.
D	The Disengaged	This group may be struggling with the material or lacking interest in the coursework. They might need interventions to address potential learning difficulties or to find ways to make the content more engaging for them.	Very low engagement and completion rates, no data on grades, indicating significant disinterest or challenges
F	Diligent Worker	Hardworking and consistent, these students might benefit from targeted help in areas where they struggle to boost their grades further.	Good engagement and fairly high grades, though not perfect, which indicates diligence and consistent effort.
G	Inconsistent Strugglers	This group likely faces challenges that may be cognitive, motivational, or based on external factors. They would benefit significantly from personalised support, more structured learning experiences, and possibly interventions aimed at identifying and overcoming their specific barriers.	Lower engagement with the lowest grades and highly variable time spent and completion rates, suggesting inconsistencies in their study habits or understanding.

B: LLM-generated recommendations for educational strategies

Targeted Interventions	Clusters showing lower engagement (Clusters A, D, and G) could benefit from interventions aimed at increasing motivation and addressing specific educational challenges.
Enhanced Support	Providing additional resources, tutoring, or personalised learning plans for Clusters C and F could help address their struggles.
Challenge and Enrichment	Clusters B and E, showing high achievement and engagement, might benefit from advanced coursework or enrichment activities to ensure they remain challenged and engaged.
Engagement Strategies	For clusters with high completion but lower engagement (Cluster B), interactive and engaging teaching methods could make learning more appealing and effective.
Regular Assessments	Frequent formative assessments could help in identifying areas where each cluster may need specific help, allowing for timely interventions tailored to their needs.

Conclusion

Our current work with Scoutlier EngagED in diverse, experiential STEM learning settings is providing early indications that multi-model student learning data can be utilised to provide insights into learning engagement. Importantly, it shows that these data can be used to find patterns from which intuitive insights can be generated that provide teachers insights into how their students are engaging and performing, and how they might enhance their learning experience and outcomes. While still highly preliminary, we are encouraged by the potential of EngagED and similar tools to transform STEM education by leveraging data-driven insights to create more engaging, personalised, and inclusive learning environments that enhance both student motivation and academic performance.

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Disclosure of the use of AI-assisted technologies during writing

No AI-assisted technologies were used during the writing process.

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Dr. Kathryn Jessen Eller is a research scientist at The Concord Consortium, a non-profit that expands and deepens STEM inquiry through open educational resources. With extensive experience in K-16 teaching, professional development, and curriculum design, Kathy leads two federally funded programs: an NSF ITEST project introducing high school students to data science, artificial intelligence, and healthcare via a social justice lens, and an Office of Naval Research initiative bringing ocean exploration, robotics, and programming to secondary students. Her MS and PhD research at the University of Connecticut and postdoctoral work at The Marine Biological Laboratory/Tufts University examined pollutants' impact on marine life using histopathological and biomolecular methods. Kathy promotes STEM literacy – particularly in biology, data science, and AI – via her research and decades of environmental and educational community service. She is particularly interested in increasing the representation of under-resourced and underrepresented groups in STEM.

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