AI-Driven Climate Resilience Education: A Framework for Predictive Thinking in Engineering Classrooms

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Abstract

Engineering education often emphasizes design and analysis while giving limited attention to predictive and adaptive decision-making in response to climate change. As transportation systems face increasing weather-related disruptions, there is a growing need to prepare future engineers to reason about climate resilience using data-driven tools.

This work introduces the AI-Driven Climate Resilience Education (AICRE) framework, a pedagogical approach designed to support climate-resilient engineering decision-making through the use of artificial intelligence and real-world data. The framework was implemented as a work-in-progress instructional approach within an undergraduate engineering course focused on data-driven systems analysis. In this context, AI techniques serve as analytical tools to help students interpret climate-related data, anticipate system disruptions, and evaluate adaptive responses.

Students will engage in project-based learning activities using datasets from the Federal Aviation Administration and Open-Meteo Statistics to examine weather-induced disruptions in air transportation systems. Guided modules introduced students to predictive modeling concepts, including logistic regression and random forest methods, as a means of supporting climate-informed decision-making rather than as standalone technical outcomes. Evaluation methods will include pre- and post-activity surveys, reflective journals, and analysis of team project artifacts.

Preliminary observations from the ongoing implementation drawn from qualitative coding of student activity responses (N = 17), indicate considerable variation in student engagement across the framework's four components. Uncertainty communication about model limitations emerged broadly across the cohort, with 59% of students acknowledging prediction error or the conditional nature of model outputs without direct prompting. However, the predictive interpretation component which requires reasoning about future system behavior under changing climate conditions showed the lowest activation rate, with 47% of students producing no substantive response. These findings point to specific instructional refinements needed to support the full AICRE learning cycle in future implementations.

1. Introduction

Engineering education has traditionally emphasized design, modeling, and analytical techniques, often treating uncertainty as a secondary concern rather than a central feature of engineering practice. At the same time, climate change is altering the operating conditions of many engineered systems, particularly large-scale transportation networks that must function reliably under increasing weather variability and extreme events. Reports from the Intergovernmental Panel on Climate Change have highlighted the increasing frequency and severity of climate-related disruptions, as well as the need for adaptive responses across various technical systems [1]. Preparing engineering students to reason about such uncertainty remains an uneven aspect of undergraduate education.

In response to these challenges, engineering programs have increasingly incorporated sustainability and resilience into their curricula. Prior work in engineering education emphasizes that resilience involves not only robust design but also informed decision-making under changing and uncertain conditions [2]. However, undergraduate instruction often introduces uncertainty through simplified assumptions or static examples, rather than through engagement with real data that reflects evolving system behavior. As a result, students may graduate with strong analytical skills but limited experience applying those skills to climate-sensitive decision contexts.

Artificial intelligence and data analytics are now widely used to examine climate-related disruptions in engineering practice. In educational settings, these tools are frequently introduced as technical competencies, with emphasis placed on algorithms, model performance, and computational workflows. While such instruction is valuable, several studies in engineering education suggest that learning is deepened when analytical tools are embedded within authentic, decision-focused problems rather than taught in isolation [3]. For climate-resilient engineering, predictive models are most effective when they support interpretation, judgment, and adaptation, rather than serving as standalone instructional endpoints.

This paper presents a Work-in-Progress instructional framework, AI-Driven Climate Resilience Education (AICRE), developed to address this gap. The framework is being implemented in an undergraduate engineering course focused on data-driven systems analysis. AICRE positions predictive modeling as an analytical support tool that enables students to examine climate-related disruptions and connect data-driven insights to engineering decisions about system resilience. The framework draws on principles of project-based learning, which have been shown to promote engagement and integrative reasoning when students work with authentic datasets and open-ended problems [4]. As an ongoing implementation, data collection focuses on student artifacts, reflections, and evidence of predictive reasoning and decision-making. The sections that follow describe the AICRE framework, its initial course integration, and the methods used to document early educational outcomes.

2. Background and Related Work

Engineering practice increasingly requires professionals to operate under conditions shaped by climate variability, uncertainty, and evolving system constraints. In response, engineering education has expanded its attention to sustainability and resilience, particularly in disciplines connected to infrastructure and transportation systems. National and international reports emphasize that resilience involves not only robust design but also the capacity to anticipate disruptions, interpret data, and adapt decisions as conditions change [1], [2]. These expectations place new demands on how undergraduate engineers are prepared for practice.

Within engineering education, sustainability and resilience are most commonly addressed through design-oriented activities, such as lifecycle assessment, environmentally conscious materials selection, and resilient infrastructure design projects [5]. While these approaches are valuable, they often emphasize static design choices rather than operational decision-making under uncertainty. As a result, students may gain awareness of sustainability goals without developing the skills needed to reason about dynamic system behavior in the presence of climate-related disruptions.

At the same time, data analytics and predictive modeling have become increasingly visible in engineering curricula. Courses in systems engineering, computing for engineers, and data science frequently introduce students to predictive tools and machine learning workflows [6]. Much of this instruction focuses on technical competence, including model construction, evaluation metrics, and algorithmic comparison. Although these skills are important, prior work suggests that learning outcomes are strengthened when analytical tools are embedded within meaningful problem contexts that require interpretation, judgment, and reflection [3].

Project-based and problem-based learning approaches have been widely studied in engineering education and are consistently associated with improved engagement and deeper understanding, particularly when students work with authentic datasets and open-ended problems [4], [7]. These environments encourage students to move beyond procedural analysis toward integrative reasoning. However, relatively few documented instructional frameworks explicitly position predictive modelling as a supporting mechanism for climate-resilient engineering decision-making. Most existing approaches treat either sustainability or data analytics as primary learning goals, rather than connecting predictive insights directly to adaptive decision processes.

The AICRE framework builds on prior research in sustainability education, data-informed pedagogy, and project-based learning by explicitly linking predictive analysis to questions of system resilience. Rather than framing artificial intelligence as the instructional endpoint, the framework situates predictive tools within a broader educational objective: helping students reason about climate-induced disruptions and evaluate adaptive responses using real-world data. In doing so, AICRE addresses a gap in current engineering education literature by emphasizing decision-making under climate uncertainty as a central learning outcome.

3. AICRE Framework Design

The AI-Driven Climate Resilience Education (AICRE) framework was developed to support climate-resilient engineering decision-making by embedding predictive analysis within instructional activities that emphasize interpretation, judgment, and adaptation. Rather than introducing artificial intelligence as a standalone technical subject, the framework treats predictive modeling as an analytical aid that supports student reasoning about system behavior under climate uncertainty.

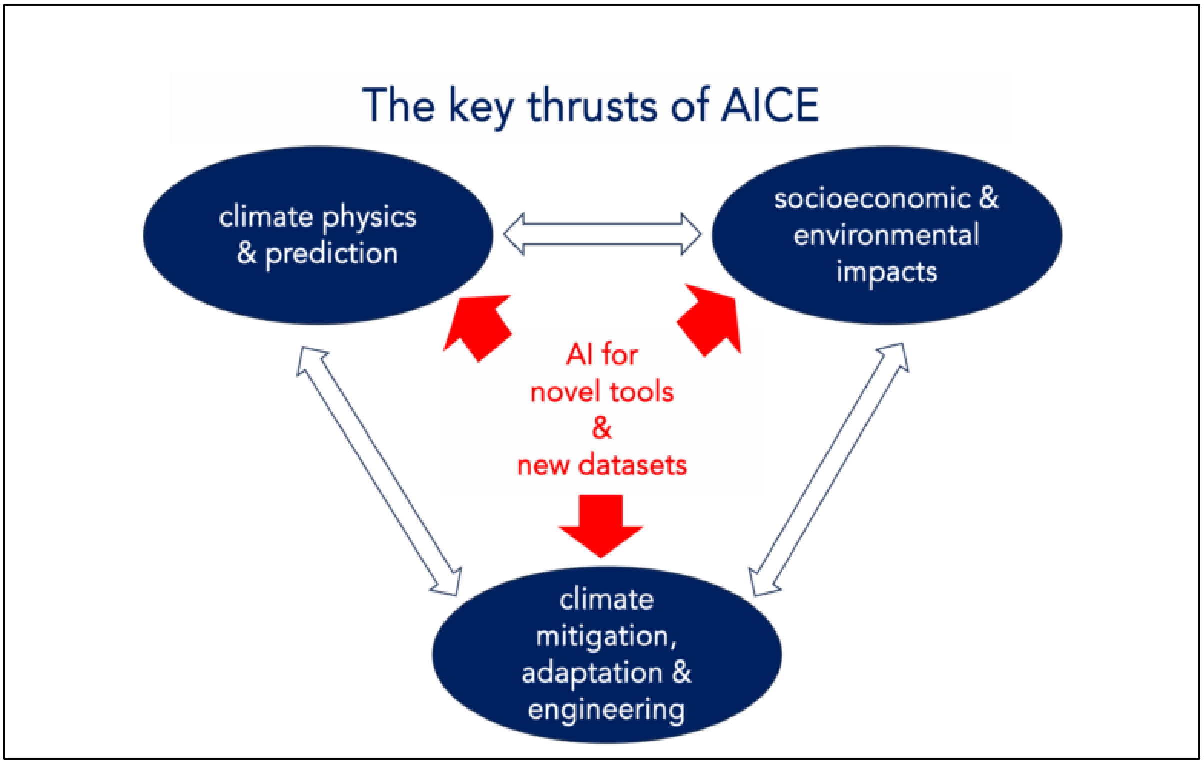

Figure 1. *Conceptual structure of the AI-Driven Climate Resilience Education (AICRE) framework, showing the iterative relationship between contextual grounding, data-driven analysis, predictive interpretation, and decision-focused reflection, centered on climate-resilient engineering decision-making.*

Figure 1 illustrates the conceptual structure of the AICRE framework. The framework is organized around four interconnected components; contextual grounding, data-driven analysis, predictive interpretation, and decision-focused reflection, arranged as an iterative cycle surrounding the central objective of climate-resilient engineering. The circular structure emphasizes that decision-making in climate-sensitive systems is not linear, but instead requires repeated movement between context, analysis, interpretation, and reflection as conditions evolve.

The first component, *contextual grounding*, situates learning within a realistic engineering problem shaped by climate variability. In the current work-in-progress implementation, this context is drawn from transportation systems affected by weather-related disruptions. Students are introduced to system constraints, performance objectives, and climate-related stressors before engaging in any computational analysis. This stage establishes the decision context and frames subsequent analytical work as a response to an identified engineering challenge.

The second component, *data-driven analysis*, engages students with authentic datasets related to system performance and climate conditions. Students explore variability, trends, and relationships within the data using basic predictive modeling tools. Methods such as logistic regression and random forest models are introduced at this stage not as learning endpoints, but as mechanisms for examining how climate variables relate to system disruption. Instructional emphasis remains on understanding inputs, outputs, and limitations rather than algorithmic optimization.

The third component, *predictive interpretation*, focuses on connecting model outputs to engineering meaning. Students examine predictions in terms of likelihood, uncertainty, and potential system impacts. Scenario-based activities, such as adjusting climate variables to represent more extreme conditions, help students explore how predictive insights inform expectations about future system behavior. This component reinforces the idea that predictive models support, but do not replace, engineering judgment.

The final component, *decision-focused reflection*, requires students to translate analytical insights into engineering considerations. Reflection activities prompt students to consider how predictive information might influence operational decisions, system adaptation strategies, or resilience planning. By explicitly linking predictive analysis to decision-making, this component shifts the learning focus away from technical execution and toward responsible engineering practice.

As shown in Figure 1, these components operate as a continuous cycle centered on climate-resilient engineering. The framework is intentionally modular and adaptable, allowing instructors to adjust the depth of modeling or duration of activities based on course context. As a Work in Progress, the AICRE framework is currently being refined through initial classroom deployment, with ongoing attention to how students move between analysis and decision-making within climate-sensitive scenarios.

4. Work-in-Progress Implementation Context

The AICRE framework was tested in an undergraduate engineering course focused on data-driven systems analysis. The students in the class had some background in programming and basic data analysis. Because of time limitations, the activity was designed to fit into a single class session of about one hour.

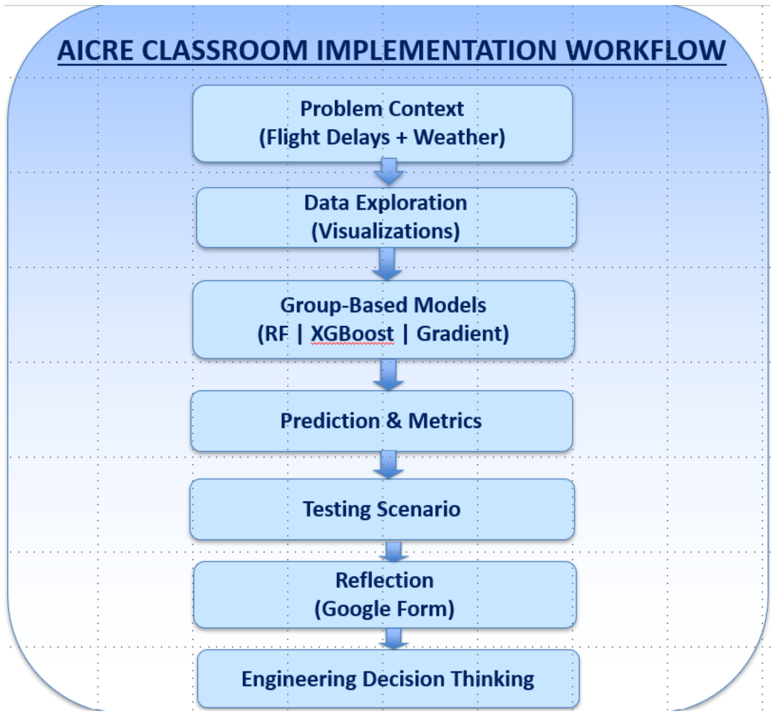

Figure 2. Classroom implementation workflow of the AICRE framework, illustrating the sequence of activities from problem context and data exploration to model interpretation, scenario testing, and decision-focused reflection.

The activity focused on a real-world problem flight delays and how they are affected by weather conditions. Students explored how factors such as temperature, precipitation, and wind can influence transportation system performance. The goal was to help students think about how changing climate conditions can affect system behavior and how engineers can respond to those changes.

Students worked with publicly available flight delay data combined with weather data from open sources. The dataset included variables such as temperature, precipitation, wind speed, and delay indicators. Basic data cleaning and preparation were done before the class so that students could focus on understanding the results rather than spending time on setup.

To make the session more interactive and manageable within the limited time, students were divided into small groups. Each group was assigned to a different predictive model, including Random Forest, XGBoost, and gradient-based models. Instead of building models from scratch, students were given guided code and asked to run the models, observe the outputs, and think about what the results mean.

During the activity, students looked at simple visualizations, ran the provided models, and reviewed performance measures such as accuracy and confusion matrices. They were also asked to explore a short scenario by adjusting one weather variable, such as increasing temperature or precipitation, and observing how the predictions changed. This helped them think about how future climate conditions might affect system performance.

At the end of the activity, students completed a short Google Form. The questions focused on what they observed, how they understood the model results, and what decisions they would make as engineers based on those results. The emphasis was on interpretation and reasoning, not technical coding skills.

Since this is still a work in progress, the activity was kept simple and flexible so it can be adapted to other classes. Even within a short time, the structure allowed students to engage with real data, compare different models, and think about how data can support engineering decisions under uncertain conditions.

5. Assessment Approach and Data Collection

The goal of the assessment was not to measure student performance in a strict or graded way, but to understand how students engage with data, models, and decision-making. The focus was on capturing how students interpret results and how they think about engineering decisions in the context of climate-related uncertainty.

To collect this information, a simple and structured approach was used. At the end of the activity, students completed a short Google Form. The questions were designed to guide students to reflect on what they observed during the activity, how they understood the model outputs, and how they would apply those results in an engineering context. The form included a mix of short and open-ended questions, allowing students to explain their thinking in their own words.

Even though all students worked with the same dataset, they were divided into groups and assigned different models. This created some variation in the outputs they observed, which helped reveal how students interpreted different results. More importantly, the responses provided insight into how students made sense of the predictions, rather than just what the predictions were.

To make sense of the responses, a simple evaluation approach was used. Student answers were reviewed to identify key patterns in how they:

- interpreted model outputs and connected them to system behavior (Data-Driven Analysis)
- framed the problem within a real-world engineering context (Contextual Grounding)
- reasoned about how changing climate conditions would affect future system performance (Predictive Interpretation)
- translated analytical findings into engineering decisions or adaptive strategies (Decision-Focused Reflection)

Rather than using complex statistical methods, the responses were examined descriptively. The goal was to identify common themes in student thinking and to understand how the activity supported their ability to reason about data and decisions. This approach is consistent with the exploratory nature of a work-in-progress study.

Instructor observations during the session were also considered. These included how students interacted in groups, the types of questions they asked, and how they approached the scenario-based tasks. These observations helped provide additional context when interpreting the student responses.

To structure the analysis of student responses, a deductive coding framework was developed, organized around the four components of the AICRE framework: Contextual Grounding (CG), Data-Driven Analysis (DA), Predictive Interpretation (PI), and Decision-Focused Reflection (DR). Each response was rated on a three-point scale (0 = no evidence, 1 = emerging evidence, 2 = clear, elaborated evidence). Given the exploratory nature of the implementation and the small sample size, results are treated descriptively rather than through inferential statistical methods. The coding approach is intended to surface early patterns in student reasoning and to identify specific areas where instructional design may benefit from refinement in subsequent implementations.

6. Preliminary Observations and Expected Outcomes

Preliminary observations reported in this section from responses collected through a structured classroom activity form administered at the conclusion of the pilot module (N = 17). Responses were analyzed using a deductive coding framework organized around the four components of the AICRE framework: Contextual Grounding (CG), Data-Driven Analysis (DA), Predictive Interpretation (PI), and Decision-Focused Reflection (DR) -and rated on a three-point scale (0 = no evidence, 1 = emerging evidence, 2 = clear, elaborated evidence). Because this implementation is ongoing and limited to a single course context, findings are treated as descriptive and exploratory rather than conclusive. The score distributions across all four components are summarized in Table 1.

Table 1. Score Distribution Across AICRE Framework Components (N = 17)

Component	Score 0 (No Evidence)	Score 1 (Emerging)	Score 2 (Clear)	N	% Score 2
Contextual Grounding (CG)	0	12	5	17	**29%**
Data-Driven Analysis (DA)	5	9	3	17	**18%**
Predictive Interpretation (PI)	8	4	5	17	**29%**
Decision-Focused Reflection (DR)	4	7	6	17	**35%**

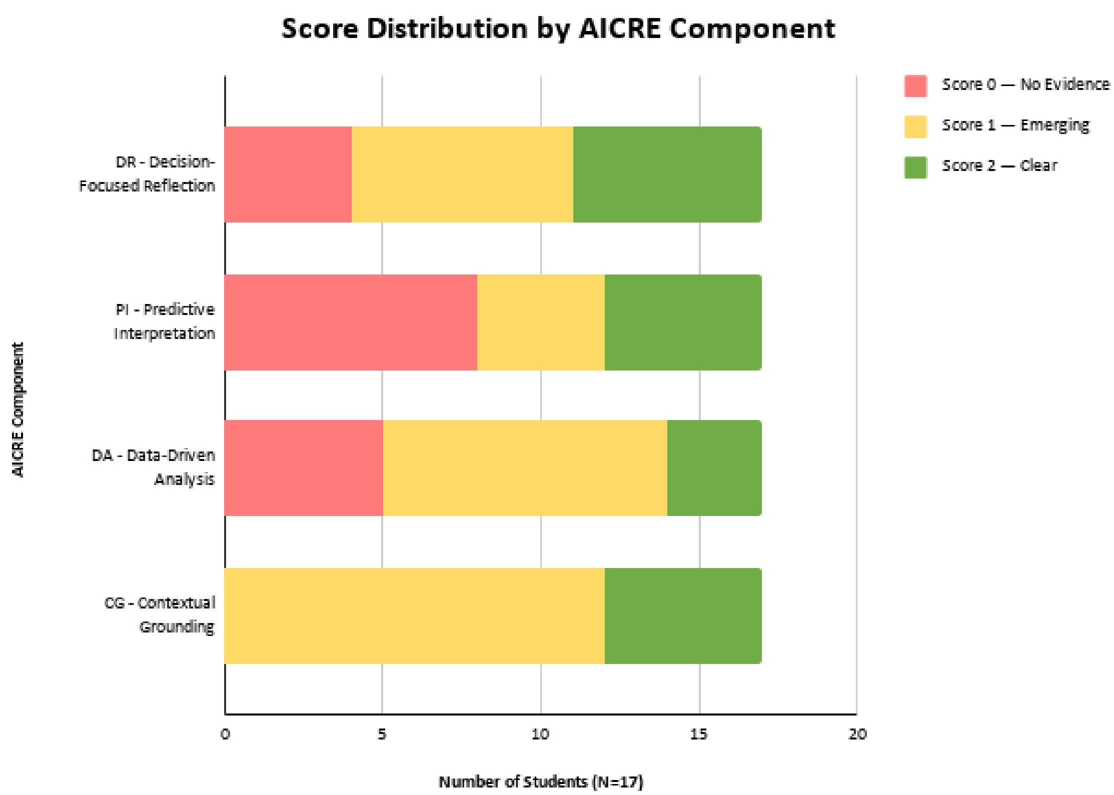

Figure 3: Score Distribution by AICRE Component

It can be observed that several patterns are apparent. An example is contextual Grounding, which produced no zero scores, indicating that the aviation setting was sufficiently concrete for all students to engage with the problem at some level; however, the majority (12 of 17) remained at the emerging level, describing single-factor patterns without extending to the multi-element systems framing that characterizes elaborated contextual reasoning. Data-Driven Analysis was more variable: five students (29%) produced no meaningful interpretation of model outputs, often naming the algorithm rather than engaging with what the predictions suggested, or reproducing numerical values without extracting analytical meaning from them. Three students (18%) demonstrated metric-aware interpretation - engaging correctly with precision, recall, and AUC values at a level that went beyond the activity's direct instruction. Decision-Focused Reflection showed the most favorable distribution, with six students (35%) producing concrete, analysis-grounded engineering recommendations, suggesting that the prompt structure for engineering action was reasonably effective even within the short module format.

The most critical pattern concerns Predictive Interpretation, which produced the highest proportion of zero scores (8 of 17 students; 47%) and was the component most frequently left unaddressed. The question asking students what their variable-modification results suggested about future system disruptions under climate change was the most commonly skipped or non-substantive response in the dataset. Several students who successfully interpreted current model outputs did not extend that reasoning to future climate scenarios, and two responses produced directionally incorrect claims about the relationship between climate change and flight delays. This pattern indicates that the module, in its current short-duration form, does not yet provide sufficient scaffolding for students to move from interpreting present predictions to reasoning about future conditions -a transition that is central to the AICRE framework's learning objectives.

The following contrasting responses illustrate the breadth of variation across the dataset. The first reflects elaborated reasoning across all four components; the second reflects procedural engagement that did not move beyond describing what the visualization showed.

Integrated Reasoner (Cluster A)	*"Data guides decisions in uncertain conditions, but it does not remove uncertainty. Patterns increase or decrease risk, but they do not guarantee outcomes. I should use model predictions to estimate risk levels and plan accordingly, not treat them as exact answers." (P11, Q8)*

Surface Engager (Cluster D)	*"I would try to reduce the delays so that we can see a little change in the charts and heat maps." (P01, Q7)*

Despite this variation, one consistent positive signal emerged across the cohort: 10 of 17 students (59%) communicated some form of uncertainty awareness without being directly prompted -acknowledging model limitations, the conditional nature of predictions, or the need for judgment beyond what the data alone could provide. This breadth of uncertainty communication, even among students who did not achieve elaborated scores on other components, suggests that short-duration engagement with the AICRE framework can begin to shift students toward treating predictive tools as decision-support instruments rather than authoritative answers. Continued implementation will prioritize adding an explicit instructional bridge between current model interpretation and future climate scenario reasoning, refining the reflection prompts to better differentiate between procedural and engineering-level responses, and extending the module duration to allow the iterative cycle of analysis, interpretation, and reflection to develop more fully

7. Discussion, Limitations, and Future Work

The preliminary analysis of student activity responses offers early evidence that the AICRE framework can activate meaningful engagement with climate-resilient engineering reasoning, even within a short-duration module. Coding of responses across all four framework components revealed that student engagement was not uniform: four distinct learner profile clusters emerged from the dataset, ranging from students who produced fully integrated reasoning across all components to students who engaged primarily at the procedural level without connecting data outputs to engineering decisions. Table 2 summarizes these clusters. The presence of all four profiles within a single cohort is itself an informative finding -it confirms that the framework's short-module implementation reaches students with significantly different entry points, and that a single instructional design will not serve all of them equally.

Table 2. Learner Profile Clusters Identified from Coded Responses (N = 17)

Cluster	Label	N	Share	Key Instructional Need
A	Fully Integrated Reasoners	4	24%	Extension challenges; ready for deeper climate scenario modelling
B	Technical Specialists	1	6%	Broaden contextual grounding beyond model mechanics to system impact
C	Moderate Engagers	7	41%	Scaffold transition from directional reasoning to scenario-based interpretation
D	Surface Engagers	5	29%	Entry scaffolding to distinguish describing outputs from interpreting the system

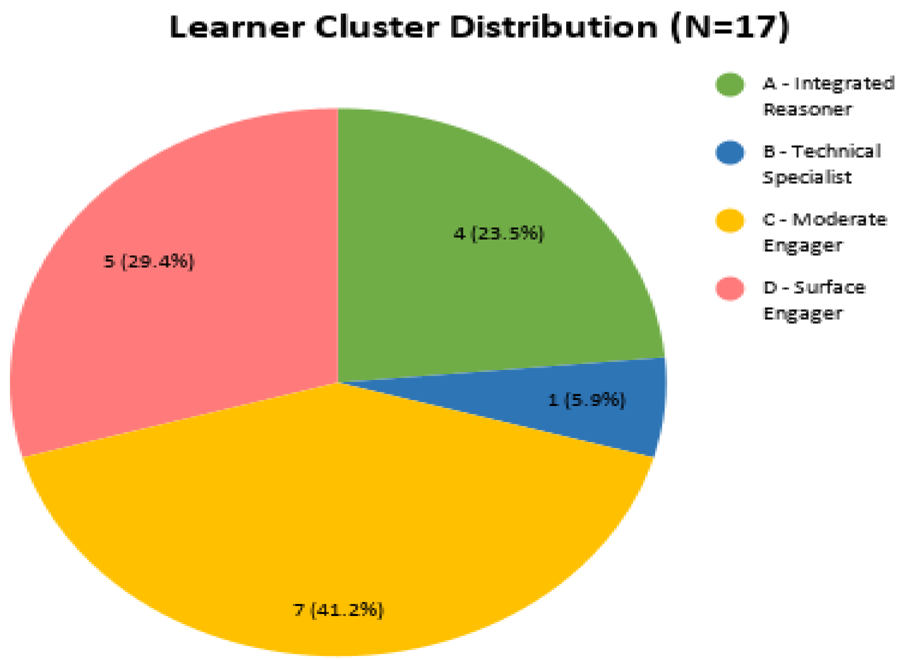

Figure 4: Learner Cluster Distribution

Two findings from the analysis carry the most direct implications for framework design. First, the Predictive Interpretation component produced the highest proportion of zero scores (47%) and was most frequently left unanswered, specifically at the question connecting variable-modification results to future climate disruptions. This is the component that most directly operationalizes the AICRE framework's core learning objective -reasoning about system behavior under changing conditions -and its low activation rate in the current implementation points to a specific instructional gap rather than a general student limitation. Second, uncertainty communication emerged as the most widely distributed outcome across the cohort (59%), appearing even among students who did not produce elaborated scores elsewhere. This suggests that short-duration engagement with the framework can begin shifting students' epistemic orientation toward treating predictive tools as decision-support instruments, which aligns with the framework's underlying premise. Taken together, these two findings -a specific PI gap and a broadly distributed UC signal -offer a more precise account of what the current module accomplishes and where its instructional design requires targeted development.

Several limitations of this work should be acknowledged. The implementation reported here is confined to a single course context with a small number of participants and a three-day instructional window, making the findings descriptive and exploratory rather than generalizable. The qualitative coding approach provides insight into student reasoning processes but does not support causal claims about learning gains, and inter-rater reliability has not yet been formally established for the coding scheme -a step that will be required before findings can be reported with greater confidence. Additionally, the activity form responses represent one data source among several planned for the full implementation; student project artifacts and reflective writing have not yet been systematically analyzed. These constraints are consistent with the work-in-progress status of the study and reflect the formative goals of the initial deployment.

Future work will address the identified gaps through three specific refinements. First, a structured instructional prompt will be added between the variable-modification activity and the climate-disruption reflection question, providing an explicit worked example that bridges current model interpretation with scenario-based forward reasoning -directly targeting the PI gap identified in the current implementation. Second, entry-level scaffolding will be redesigned for students who engaged primarily at the procedural level, with guided observation templates intended to help them distinguish describing what the visualization shows from interpreting what it means for the engineering system. Third, formal inter-rater reliability procedures will be established for the coding framework before the next implementation cycle, and the assessment approach will be expanded to include systematic analysis of student project artifacts alongside the activity form. Broader deployment across additional course offerings and engineering disciplines will follow, with the goal of examining the framework's adaptability and refining learning objectives for different instructional contexts. Outreach-oriented adaptations for pre-college audiences remain a longer-term direction, with the current priority being a more rigorous and evidence-grounded undergraduate implementation.

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