Pedalogical

AI-Grounded Vulnerability Feedback for Non-Security CS Courses

Andrew Sanders   Gursimran S. Walia, Ph.D.
Lucas P. Cordova, Ph.D.   Teo J. Mendoza

This talk presents the Pedalogical project, a web-based platform that provides AI-generated vulnerability feedback for non-security CS courses.

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1 TL;DR

1.1 ***We propose a new tool and pedagogical approach to improve cybersecurity education.***

2 Problem & Motivation

2.1 We Need to Improve Education in Developing Secure Code

Security failures start early.
Students often learn to write code before they learn to write *secure* code.

- Software vulnerability exploitation remains a leading vector in breaches; secure coding must be integrated early [1], [2], [3].

- Teaching students to use static analyzers early is important, but is very difficult due to the complexity of the output of these tools.
- Existing static analyzers flag issues but rarely deliver **actionable, level-appropriate pedagogy** [4], [5].

2.2 Prior Findings: What We Know So Far

Empirical evidence supports this gap.

- Vulnerabilities **increase and diversify** as students progress from CS1 → advanced courses [6].

- Many CS programs lack sustained, program-wide security practice; students introduce vulnerabilities in routine coursework [6], [7], [8].

- Mismatch between vulnerabilities students actually produce and those emphasized in detection research [8], [9].

- Time pressure & functionality-first norms drive insecure patterns; targeted feedback can help [7], [9].

2.3 Research Gap

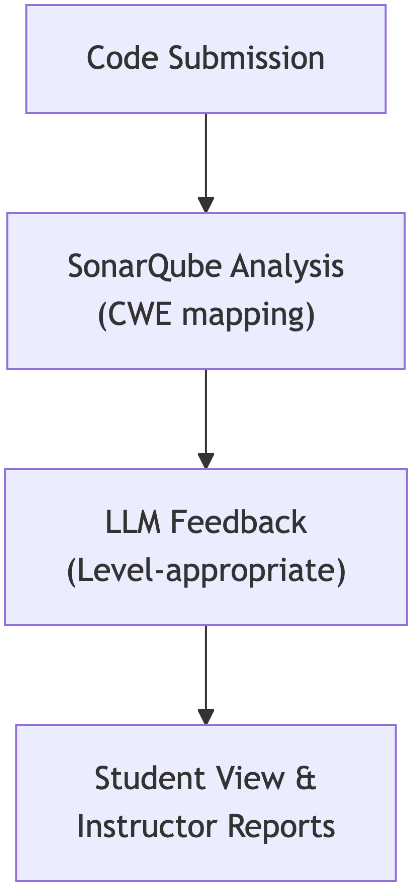
- Need an **evidence-based, scalable mechanism** that:
  - Grounds detection in a **truthful analyzer** [4]
  - **Adapts feedback** to student level (beginner → advanced) [10]
  - Supports **longitudinal study** across multiple courses/institutions
  - Collects telemetry for **learning analytics**

3 Proposed Approach

3.1 Pedalogical

- **Pedalogical** = Static Analysis (truth base) + LLM (tailored feedback)
  - Analyzer: SonarQube CE (CWE mapping) → issues & hotspots [4]
  - LLM: transforms findings into **scaffolded, actionable guidance** (tailored levels) [10]

3.2 System Pipeline



Grounded analyzer reduces hallucination risk; LLM provides audience-appropriate feedback.

3.3 Pedagogical Learning Theories

- Integrates proven learning theories into the system design to enhance the learning experience:
  - **Cognitive Load Theory** [10]: convert verbose analyzer output → concise, relevant guidance (reduce extraneous load).
  - **Zone of Proximal Development** [11]: feedback level aligned to course maturity (scaffolding).

3.4 Pedalogical Application

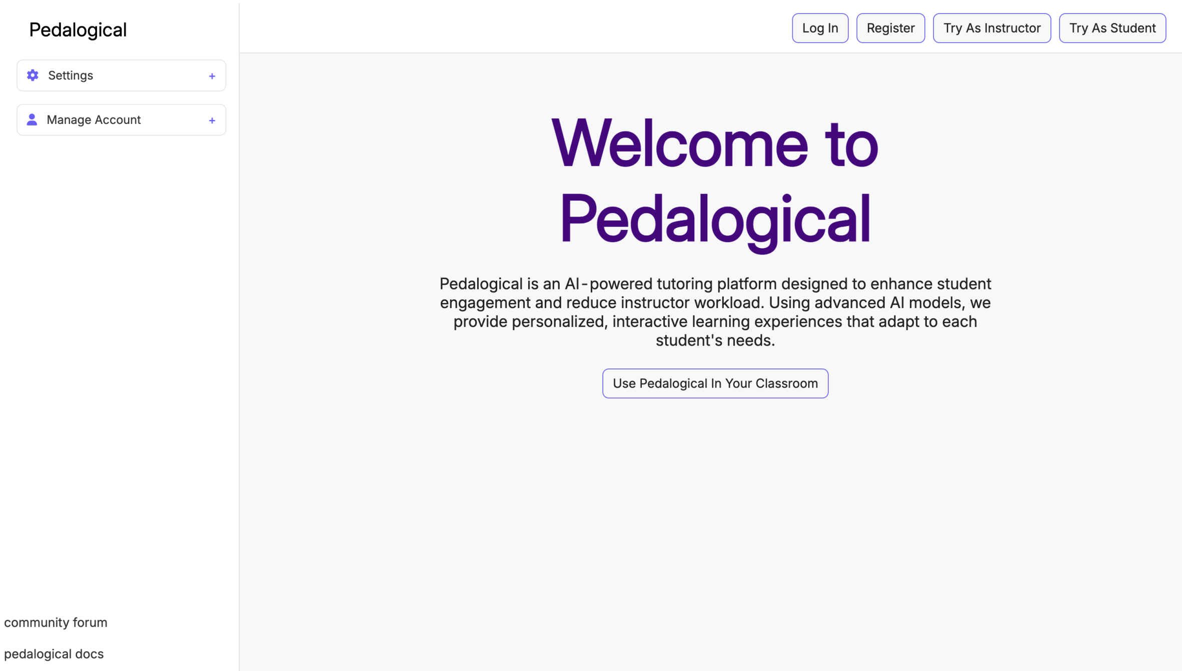


Figure 1: Figure: Pedalogical Application

3.5 Pedalogical Question Nodes

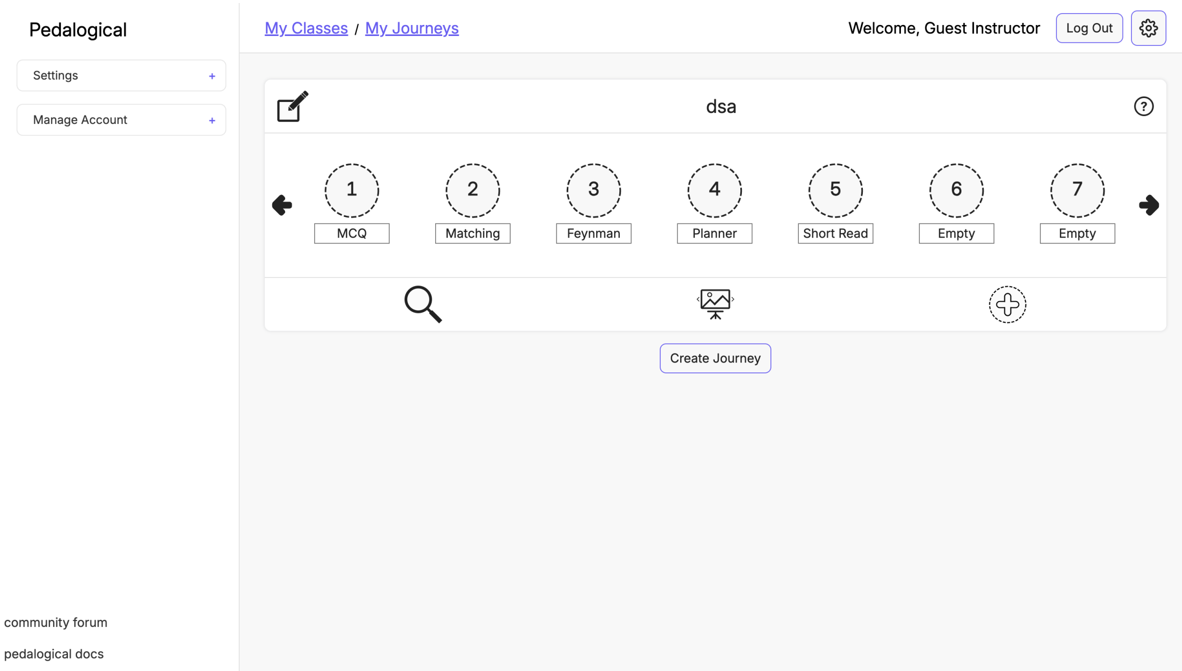


Figure 2: Figure: Pedalogical Question Nodes

3.6 Pedalogical LLM Question Generation

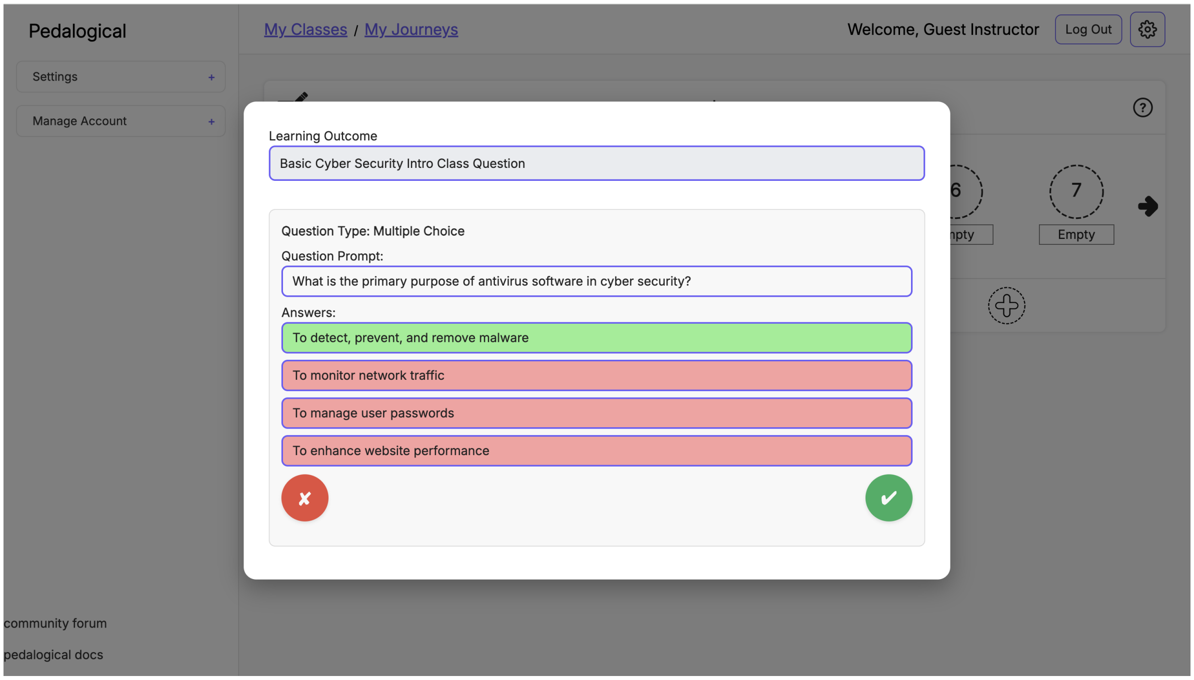


Figure 3: Figure: Pedalogical LLM Question Generation

3.7 Cybersecurity: Sample Student Feedback

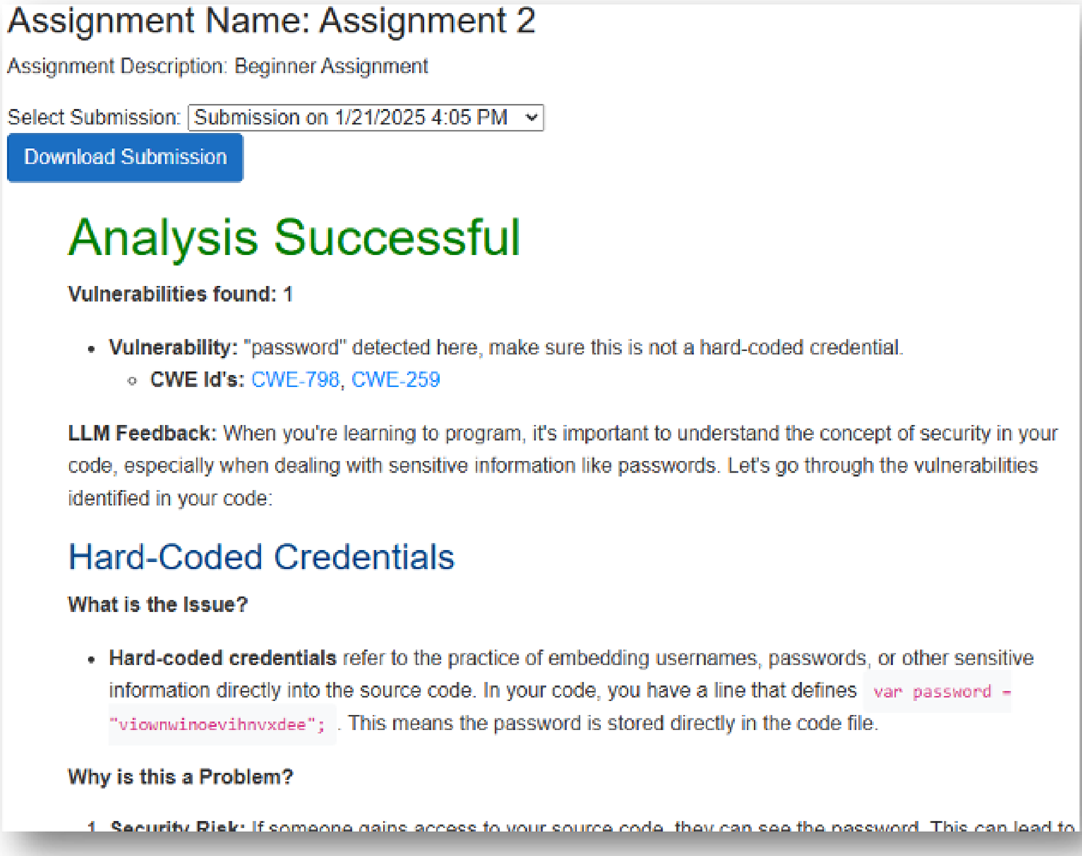
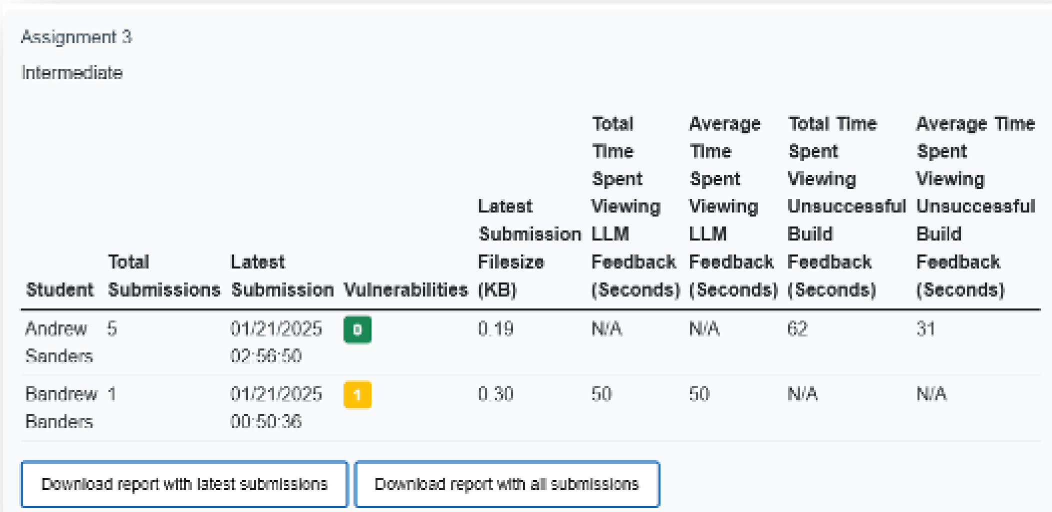


Figure 4: Figure: Sample Student Feedback

3.8 What Instructors Get

- Cohort dashboard: per-assignment vulnerability counts & trends.
- Downloadable reports: analyzer findings, prompts/responses, submission diffs.
- Configurable **feedback detail level** for scaffolding.

3.9 Sample Instructor Report



Assignment 3

Intermediate

Student	Total Submissions	Latest Submission	Vulnerabilities	Latest Submission Filesize (KB)	Total Time Spent Viewing LLM Feedback (Seconds)	Average Time Spent Viewing LLM Feedback (Seconds)	Total Time Spent Viewing Unsuccessful Build Feedback (Seconds)	Average Time Spent Viewing Unsuccessful Build Feedback (Seconds)
Andrew Sanders	5	01/21/2025 02:56:50	0	0.19	N/A	N/A	62	31
Bandrew Banders	1	01/21/2025 00:50:36	1	0.30	50	50	N/A	N/A

Figure 5: Figure: Sample Instructor Report

4 Proposed Study Context

4.1 Research Questions

RQ1: Is AI-generated vulnerability feedback associated with **reduced vulnerabilities** in revised submissions?

RQ2: Does exposure to AI-generated vulnerability feedback **improve secure coding practices** over time?

4.2 Proposed Study Context

- Multi-course, multi-institutional.
- Undergraduate courses (intro → advanced; multiple sections; in-person & online).
- Incentivized via **bonus points** contingent on meeting minimum functionality and reducing vulnerabilities.

4.3 Data & Measures

- **Static analysis artifacts:** CWE-tagged vulnerabilities, security hotspots, bugs, code smells.
- **Engagement telemetry:** time on feedback, resubmission frequency, interaction with explanations.
- **Learning signals:** pre/post patterns across assignments; regression models of engagement → reduction.
- **Qualitative:** end-of-semester survey on usefulness & strategies.

4.4 Analysis Plan

- Longitudinal within-course and cross-course comparisons.
- Regression modeling: engagement metrics → vulnerability change.
- Category-level success: which CWE types improve most?
- Sensitivity to bonus-point variability across courses (limitations acknowledged).

4.5 Expected Contributions

- A **replicable pipeline** for secure-coding feedback integrated into non-security courses.
- Evidence that **grounded LLM feedback** can reduce vulnerabilities and shape habits .
- A platform for **program-level learning analytics** on secure coding.

4.6 Anticipated Threats & Limitations

- Bonus-point schemes differ across courses → potential confounds.
- Structured prompts mitigate LLM variability, but do not eliminate it [12].

5 Encouraging Early Analysis

5.1 Pedalogical in a CS2 (Data Structures) Course

- Students designed and selected data structures for a medium-sized programming project.
- Experimental group used the Pedalogical chatbot for guided reasoning and scaffolding, while the control group used a generic ChatGPT-4.0 wrapper, enabling comparison of design quality, reasoning depth, and tool engagement.
- Students in the experimental group performed significantly better on project outcomes, suggesting increased metacognitive awareness and problem-solving strategies based on rubric-based grading.

5.2 Call to Action

- Adopt Pedalogical in non-security courses to **normalize secure coding**.
- Collaborate on **cross-institutional studies** and shared analytics.
- Extend to additional languages & rulesets; explore adaptive feedback policies.

6 Thank You!

6.1 Contact Information

Lucas Cordova

- lpcordova@willamette.edu
- lpcordova.com

7 References

7.1 References

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