FEEDBOT: Formative Design Feedback on Programming Assignments

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Abstract

This paper describes FEEDBOT, an open-source formative assessment tool leveraging large language models (LLMs) to provide structured, high-level feedback on open-ended programming assignments. Designed to both address the limitations of traditional autograding and overcome scaling challenges of formative assessment, FEEDBOT uses an existing pedagogical framework to provide targeted but limited actionable feedback. Early results demonstrate measurable improvements in student performance in a large introductory computer science course, while avoiding the pitfall of providing too much assistance that more unstructured tools commonly encounter. While this experience report merely captures our particular use of this tool, we believe either the tool or the approach it takes is readily adaptable to many other contexts.

CCS Concepts

• **Applied computing** → **Education**; • **Computing methodologies** → **Artificial intelligence**.

Keywords

formative, autograding, llm, feedback, education

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1 Introduction

Formative assessment[3], which allows students to iteratively improve their work based on feedback, is vital for fostering deep learning and reducing educational inequities. However, traditional formative assessments are challenging to implement in the large classes typical to introductory computer science due to resource constraints. In particular, allowing students to resubmit, even a limited number of times, multiplies the already significant grading load in large classes, rendering this approach nearly non-viable in case of manual grading.

Automated grading systems, where most exploration of formative feedback within computer science courses has been, alleviate the grading effort challenge, but these traditional autograders, based primarily on unit testing, require rigid assignment structure and thus severely limit not only the type of feedback that can be provided but even the type of assignments that can be given. This means that important learning goals like being able to address open ended data design problems or problems that involve non-trivial decomposition into sub-problems may be impossible to include if unit test-based autograding is a requirement.

To bridge this gap, FEEDBOT leverages large language models (LLMs) to provide automated structured feedback on a variety of open-ended programming assignments, including both data design and function design. In order to do this, it relies upon students following a step-by-step approach when solving problems. While many pedagogical tools that exist use LLMs, FEEDBOT is unique in that it provides both very specific feedback but without giving away even parts of solutions.

In order to do this, it relies upon the fact that the pedagogical approach used in the course, the Design Recipe [5, 14], breaks the problem solving process of designing data definitions and designing functions into sequential steps, so that FEEDBOT is tasked with identifying exactly what step (if any) that the student's solution has gone wrong on.

Briefly, the Design Recipe proceeds as follows: data design is accomplished by (1) identifying the values that make up the data, (2) describing (in a comment) how the data will be used in the program, (3) writing down examples of the data, and (4) constructing an example function "template" showing how the data might be used. Function design is done by (1) describing the input and output types of the function, (2) writing down a concise statement (in English) of what the function does, (3) writing example function uses (test cases), and (4) implementing the function.

Since FEEDBOT knows whether a given problem is a data design problem or a function design problem, its task is to: (1) assess whether all four steps have been completed satisfactorily and if not, (2) identify the first step that needs work. Since the steps are

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intentionally sequential, the first step with issues is the ideal place for a student to begin fixing their work. Additionally, since the steps are quite granular, the mere identification of that step strikes a good balance of giving students guidance without giving them so much assistance that they do not learn from doing the work on their own. While FEEDBOT is certainly not bound to the Design Recipe, its success is certainly due to the sequential and granular nature of this pedagogical framework, and likely without it the tool would have similar struggles to other tools in this space.

1.1 Contributions

This paper makes the following contributions:

(1) **Tool Design:** Introduction of FEEDBOT, a novel open-source tool leveraging LLMs to provide structured feedback tailored to programming assignments.
(2) **Pedagogical Integration:** Demonstration of how FEEDBOT both relies upon and benefits from an existing pedagogical framework (the Design Recipe of Felleisen et al. [5]).
(3) **Evaluation of Effectiveness:** Analysis of the impact of FEEDBOT on student performance, with initial evidence showing measurable improvements in learning outcomes. While this analysis is limited (and only covers a single iteration of use of the tool), we present this as an experience report for others to build upon.
(4) **Scalability and Reproducibility:** Exploration of FEEDBOT 's potential to support large-scale courses, highlighting challenges and guidelines for adoption or adaptation.

1.2 Structure of paper

The remainder of this paper is structured as follows:

- §2: **Related Work** explores existing literature on formative assessments, autograding systems, and the use of LLMs in education, identifying gaps that FEEDBOT addresses.
- §3: **Implementation** outlines the design, methodology, and key features of the tool.
- §4; **Findings and Results** presents both quantitative and qualitative analyses of FEEDBOT 's effectiveness.
- §5: **Conclusion** summarizes key contributions, findings, and directions for future work.

2 Related Work

The potential of generative AI technologies, particularly large language models (LLMs), in enhancing teaching and learning practices has been increasingly recognized. Baidoo-Anu and Owusu Ansah [1] explored the application of ChatGPT in promoting education, highlighting its role in fostering accessibility and engagement in classrooms through personalized interactions and immediate feedback mechanisms.

Mastery learning, introduced by Bloom [3], provides a theoretical foundation for formative assessment approaches, focusing on achieving mastery of topics through iterative improvement. Building upon these principles, Felleisen et al. [5] introduced the Design Recipe, a structured methodology that guides students in problem solving and program design. The Design Recipe's focus on concreteness fading, a method reviewed systematically by Fyfe et al. [6], demonstrates the educational benefits of gradually transitioning from concrete to abstract representations in teaching programming concepts.

Recent research has evaluated the effectiveness of LLMs in supporting students' learning processes. Hellas et al. [8] analyzed how LLMs respond to beginner programmers' help requests, finding potential in their ability to scaffold learning but identifying challenges in addressing misconceptions.

Garcia et al. [7] and Lionelle et al. [12] emphasized the scalability of LLM-driven feedback in large courses, introducing grading frameworks that balance formative and summative assessment needs.

Ren et al. [13] provided insights into the types of help students seek during TA office hours, a study that informed the integration of structured feedback mechanisms in tools like FEEDBOT. Complementing this, Tuson and Hickey [16] proposed mastery-based grading systems with specifications (specs) grading, aligning assessments with well-defined, modular learning outcomes.

There have also been many LLM-powered tools developed. CodeHelp, developed by Liffiton et al. [11, 15], leverages LLMs to provide scalable support with embedded guardrails to ensure pedagogical alignment. This tool was further studied by Denny et al. [4] (in a limited, 13 day period), where they collected significant qualitative feedback from students. Highlights from that support the design of FEEDBOT– that AI assistants should guide students where to work but should not solve problems for them. Unlike FEEDBOT, CodeHelp provides open ended feedback and thus is somewhat prone to assisting too much (partially addressed by introducing keyword blacklists). This is, of course, a tradeoff, as FEEDBOT does not have a mechanism to explain concepts, which a more general "AI Assistant" clearly would have to.

A similar tool is CodeAid [10], which adopts the strategy of only explaining in terms of pseudocode, but still explains in high levels of detail how to solve problems, and thus possibly stands in for significant student learning, unlike FEEDBOT. Giving solutions as pseudocode and leaving the only learning task a translation to real code seems a real detriment.

Bassner et al. [2] built Iris, which allows open-ended questions but filters them using extensive prompting via a similar strategy as FEEDBOT to ensure that the output does not contain solutions or too much help. It is a much heavier weight solution, as it requires integration into an interactive learning platform, and unlike FEEDBOT, which suggests a place where a student has made a mistake, Iris doesn't provide assistance outside of what students explicitly ask for.

Jacobs and Jaschke [9] built Tutor Kai, which gives feedback on programming tasks, but with single functions and with extensive feedback. Perhaps partly due to the model (GPT-4) or partly due to the level of detail in the feedback (unlike FEEDBOT, which simply identifies a step in the Design Recipe where a mistake occurs, Tutor Kai describes exactly what is wrong, and if there are multiple mistakes, describes all), they ran into problems with hallucinations and mistakes.

While these (and many other) tools use LLMs, most provide nearly unaltered output from LLMs, even with significant prompt engineering, which often means that there are risks of providing too much help to students. This is very different from FEEDBOT,

where the feedback is intentionally very limited: while the output from the model is extensive, we include a delimiter and then an extremely short response after it, and only display the latter to students. Because FEEDBOT fits into an existing pedagogical framework that is highly structured, it can refer students back to the step of the design process they should focus on with minimal additional help. Thus, it can use the LLM to identify where a student should focus their work, rather than telling them what to do, or even what exactly is wrong, since the step to focus on should allow them to do their own reasoning.

3 Implementation

FEEDBOT uses OpenAI's `o1-mini` to analyze student submissions and provide feedback aligned with the Design Recipe framework. FEEDBOT has been prototyped using Racket's Teaching Languages, but is not tied to Racket. It does, however, rely upon the structured and sequential approach of the Design Recipe, and in order to be adapted to a different pedagogical approach, a similar structure would have to be identified. This is because the primary feedback is pointing students to which step in the process they should focus their attention on.

3.1 Prototyping

Initial experiments were conducted using the OpenAI API (first with GPT-4-turbo-preview, and later with GPT-4o and o1-mini when those models became available). Experiments assessed the feasibility of using commercial LLMs to provide actionable feedback on student programming assignments. They demonstrated the models' capability to understand student code in the Racket Teaching Languages, identify deviations from reference solutions, and generate feedback aligned with high-level design principles.

The prompt was refined iteratively to provide more accurate and consistent feedback. Many components align with known "best practices" in prompt engineering, including:

- providing a persona for the LLM ("You are FeedBot...")
- providing a clear step-by-step process
- requesting chain-of-thought output (this was particularly effective in improving consistency, since it separated the tasks of code analysis and feedback writing)

For testing, we designed a system to generate responses with multiple prompts, multiple times per prompt, and present them side-by-side. This allowed direct analysis of differences in quality and replicability between prompt iterations.

These experiments utilized the Design Recipe framework[5]. This structured methodology not only facilitates effective feedback but also aligns with the types of assistance students typically seek from teaching assistants. While the experiments focused on the Beginning Student Language dialect of Racket, the findings suggest that the approach could be extended to other languages like Python or Java, though additional structuring may be required for providing similar pedagogically sound feedback in those contexts.

While the results from closed-source models will always be somewhat difficult to nail down concretely, we did notice a consistent problem with `GPT-4o` where it would occasionally not notice type signatures despite them being present. This issue, which we identified during the final round of testing right at the beginning of the semester, motivated the switch to `o1-mini` (which was released right at that time), which did not have the same weakness.

3.2 Prompt Structure

For each question, the final prompt was structured as follows:

```
[System prompt]
[General prompt + (Data Design or Function Design) prompt]
[Assignment Context]
[Problem Description]
[Grading Note]
[Dependent problems (Description + Student response)]
[Student response for this problem]
[Summary of request]
```

The system prompt is the standard prompt for all problems explaining the role of the LLM. The general prompt is an explanation of what the LLM should provide feedback based on (the Design Recipe) as well as the chain-of-reasoning steps. In our prompt, we ask the LLM to respond in two parts, first walking through each step of the Design Recipe and identifying if it is present or missing, and only then providing feedback to the student based on the response to the first part. Of course, we also include the exact steps we are looking for based on whether it is a Data Design or Function Design problem. The assignment context contains all the instructions in the outer problems leading up to this problem (this includes general instructions for all sub parts). After the problem description, we include the problem specific grading note (if present), and all dependencies (see §3.4). Next, the student response is included. Finally, we reiterate the task to provide the two parts, separated by the delimiter.

We found this structure provides reasonably accurate feedback, particularly due to the chain-of-reasoning style prompting, even though the particular LLM we used (OpenAI's o1-mini) already claimed to be a "reasoning model". We did make a few minor tweaks/additions to the prompt during the semester as we encountered some misleading feedback, but the structure of the prompt was unchanged. The refinement step asks the model to provide output after a delimiter, and we only provide the post-delimiter output to the student.

3.3 Demonstration

In this subsection, we show an example problem and the raw output that the prompt produces. Note, importantly, that after giving extensive feedback, it inserts a delimiter and provides a very concise summary of only the first issue, which is what is shown to the student. While this was very reliable, we also included additional failsafes like stripping markdown code from the output (as any code it the output is a bug, and code always appears inside markdown code marks).

This problem, which occurred in HW7 (see §4 for the array of assignments we ran the tool on) For an assignment on anonymizing student responses, an initial prototype of FEEDBOT was tested on multiple submissions containing various issues. The task involved converting a list of student responses containing names into an anonymized list without names, adhering to structured design

principles. Below is an example of a submission and the feedback generated by FEEDBOT according to the standard prompt we used:

Submission.

```
(define-struct student/v4 [age demographic legacy?])
;; A student/v4 is a:
;; (make-student/v4 Integer String Boolean)
;; - age: The age of the student
;; - demographic: The ethnicity of the student
;; - legacy?: Whether the student is a legacy student or not

(define STUDENT1 (make-student/v4 19 "White" #false))
(define STUDENT2
  (make-student/v4 20 "Black or African American"
                   #true))

;; anonymize: [Listof student/v4] -> [Listof student/v4]
;; Removes names from the list of students
(check-expect (anonymize '()) '())
(check-expect (anonymize (list STUDENT1 STUDENT2))
              (list STUDENT1 STUDENT2))

(define (anonymize students)
  (cond
    [(empty? students) '()]
    [else
     (cons (make-student/v4
            (student/v4-age (first students))
            (student/v4-demographic (first students))
            (student/v4-legacy? (first students)))
           (anonymize (rest students)))]))
```

Feedback. Running FEEDBOT on the above submission, which has a dependency on a prior problem (where the non-anonymized student was defined as `student/v3`) results in the following response, with what comes after the delimiter (======) shown to students:

```
### PART 1:
1. Signature for anonymize
   (a) No
  (b) The signature in [Student Code] does not correctly
   reflect the required input and output types.
2. Purpose Statement for anonymize
   (a) No
  (b) It is satisfactorily completed in [Student Code].
3. Tests for anonymize
   (a) No
   (b) Only two tests are provided; at least three are
   required.
4. Function Body for anonymize
   (a) No
  (b) It is satisfactorily completed in [Student Code].

======
The signature for `anonymize` does not correctly represent
the function's input and output types as required.
Please revise it to match the problem statement.
```

Note two important things. First, while the identification of the problem is correct – the type signature is incorrect, since the input should have been a `[Listof student/v3]` (what they defined previously, which had names), rather than the already anonymized definition with `student/v4`, FEEDBOT did not tell them exactly what was wrong. Instead, it just pointed them to the signature step, so the student would still work on their own to figure out exactly what the signature should be. Second, note that while FEEDBOT identified that the student should have included more test cases, it did not provide that feedback at all, since it had already identified an earlier step with an issue.

3.4 Dependencies

A key element to scaling FEEDBOT to realistic assignments is to support problems that depend on one another. As in the above example, sometimes in one problem students would design a data definition, and then later use it in another problem. While we wanted to provide isolated feedback for each problem to increase precision, problem dependencies need to be dealt with, and simply providing the entire assignment is not a solution and giving a single piece of feedback is not a great idea. Not only would this reduce the likelihood of good feedback, as the model would have to reason about much more code at once, but while errors on earlier steps of the Design Recipe should result in no feedback on later steps, we did not want errors on earlier problems to affect the feedback on later problems.

This meant that while we ran one query per problem, we included dependencies where necessary and included in the prompt that only the current problem should receive feedback.

To support this, we split the assignment submission files, which were ordinary text files, using particular comment delimiters (arbitrarily chosen as `;;!`, given `;` begins a line comment in Racket) into individual problems, where each problem has a description and student-produced code in response. We then used a second delimiter ";;!! Write your response below" to distinguish problem descriptions from student-produced responses, which allows us to extract just the student code, and prevent student modifications of the assignment, which occasionally happened, from interfering with our feedback.

An example outline of an assignment is shown below:

```
;;!Problem 1
Problem 1 overall description

;;!Part A
Problem 1, part A description
;;!! Write your response below

...student response...

;;!Part B
Problem 1, part B description

;;!! Write your response below

...student response...
```

```
;;!Problem 2
Problem 2 description

;;!! Write your response below

...student response...
```

To track problem types and determine which problems would get feedback from FEEDBOT, each assignment had a manually created JSON file that specified, among other things, the problem dependencies for each problem. Problems were described by *paths*, which were ordered sequences of strings following the special `;;!` delimiter. For the example above, the paths for the problems would be `["Problem 1", "Part A"]`, `["Problem 1", "Part B"]` and `["Problem 2"]`. Each problem then had an optional list of dependent problems that the LLM requires to fully understand the problem. For instance, in the example above `["Problem 1", "Part A"]` may be listed as a dependency of `["Problem 1", "Part B"]`.

If any dependencies are specified, the LLM is provided with *both* the problem description and student code for each problem in the given dependent problem paths. For convenience, problem dependencies can be partial paths. In the example above, if the entirety of Problem 1 is a dependency of Problem 2, then the incomplete path ["Problem 1"] can be made a dependency of Problem 2, which makes each sub part of Problem 1 a dependency of Problem 2.

3.5 Other Metadata

In addition to the problem paths, each problem is categorized as either a Data Design (DD) or Function Design (FD) task. We crafted specific prompts for each category, explaining what each of these "recipes" are and the expected steps that a student is required to complete for each type of problem.

Finally, problems have optional "grading notes", which allow us to include problem-specific feedback instructions. These notes are particularly helpful for problems where certain parts of the recipe are predefined or omitted. For example, if a problem includes a signature and purpose statement, students are only required to complete the tests and implementation steps. The default prompts assume all recipe steps must be completed, leading the LLM to request omitted steps due to how strongly we prompt it to ensure the student includes all steps. Reiterating that certain parts of the recipe can be omitted in the grading note for these types of problems helped resolve this issue. This also helped resolve occasional oddities, like when the model got confused about a struct field name ending in a ? and thought there was a missing function definition.

3.6 Integration into Gradescope

While the feedback from FEEDBOT was entirely unrelated to grading, we used the submission & autograder mechanism from Gradescope in order to handle student submissions. When a student submitted an assignment, in addition to ordinary autograder tests that ran before the assignment deadline, we would run the client for FEEDBOT, which was responsible for extracting problems and generating prompts according to §3.2. It would then submit those to the FEEDBOT server, which existed externally in order to defer actually running the LLM queries until students went to view the output. This was a significant cost savings, given that only around half of students viewed the results of FEEDBOT. The server also had buttons that allowed students to give feedback on the quality of response (see §4.1 for results from those). Once the prompt was submitted to the FEEDBOT server, it returned a URL that was displayed in the autograder output. When students visited the link, they would see a loading page while the query was run, and around 10 seconds later would get the feedback.

Partly to control cost, and partly because we wanted students to spend time thinking about the feedback before resubmitting, we implemented both a cooldown period and an overall rate limit. For our implementation, we only ran FEEDBOT if it had not been run in the last hour (other submissions could have occurred), and only ran a total of 5 submissions per assignment.

We implemented both using the metadata provided by Gradescope, but this turned out to be quite unreliable—while the specification provided to the autograder includes metadata about the results of its previous runs, which should have allowed us to determine when we successfully ran FEEDBOT (if the file could not be parsed, this would not happen, so we could not merely use the submission dates), but this ended up being unreliable, occasionally simply missing.

4 Findings and Results

The bulk of the development on FEEDBOT was done over the spring and summer preceding the semester whose results we are describing. While that testing was done with other models, the actual use of FEEDBOT that this experience report describes was all done with OpenAI's `o1-mini`. Due to integration details unrelated to FEEDBOT, including being unsure whether we wanted to provide the feedback from the very beginning of semester, we didn't introduce FEEDBOT until partway through the semester. We also ran it for one assignment with the results only visible to TAs in order to identify any remaining bugs in the tool or, more likely, prompt. As a result, we used it fully on seven homework assignments, in an introductory programming course with around 500 students.

4.1 Quantitative Analysis

Since the manual grading that captures the design skills that FEEDBOT was intended to aid with only happened after the assignment deadline (and only a single time), measuring the impact of FEEDBOT is challenging. We can, however, segment students on each assignment based on whether they viewed the output of the tool (at least once) and those that did not.

Table 1: Average Scores of Students

HW	Never Viewed	Viewed At Least Once	Delta
HW6	81.4% (340)	90.7% (179)	+9.3%
HW7	79.3% (232)	87.4% (283)	+8.1%
HW8	86.5% (261)	91.1% (240)	+4.6%
HW9	93.6% (301)	95.9% (211)	+2.3%
HW10	88.5% (230)	93.9% (283)	+5.4%
HW11	83.5% (288)	90.6% (218)	+7.1%
HW12	72.3% (240)	82.2% (212)	+9.9%

From that initial analysis, we find (see Table 1; counts of students are in parentheses) that those that used FEEDBOT did significantly better in almost every assignment where it was available. The outlier to this phenomenon, HW9, where the difference was only 2.3%, was an assignment where we included signatures & purpose statements (the first two parts of the design process) as part of the assignment, so students only had to write tests & implementations, both of which were assessed by a traditional autograder and visible at the same time as the results from FEEDBOT. Thus, we expect that the additional help that students got from FEEDBOT was minimal.

One potential threat to validity in this analysis is that students who use FEEDBOT may be students who are stronger, and thus the assistance from FEEDBOT might be marginal. To rule this out, we used the aggregate performance on HW1-4, where FEEDBOT was not available (HW5 had partial availability, so was eliminated from both sections), to segment students into four quartiles of even size. While usage of FEEDBOT was consistently highest in the top quartile, the improvement of scores showed up across the spectrum, and was indeed often most significant in the lowest quartile, showing that FEEDBOT was beneficial even to lower performing students, provided they actually used it. These results are shown in Table 2. In that table, for each quartile (Quartile 1 is lowest performing, Quartile 4 highest) the average score from those that didn't use FEEDBOT and the average from those that did, and in parentheses the percent of that quartile that used FEEDBOT.

There is one other place we can look for quantitative feedback: debugging feedback built into the tool. In order to identify issues with FEEDBOT, we included a mechanism where users could rate any piece of feedback as "Very Helpful", "Somewhat Helpful", and "Not Helpful". A total of 1357 responses were collected (around 5.3% of the total possible). Of those, 63% chose "Very Helpful", 15% chose "Somewhat Helpful", and 22% chose "Not Helpful".

While 22% is significant, manual review of the "Not Helpful" ratings reveals nuance. In particular, we found that 37% of those "useless" responses were associated with errors in the student submission that FEEDBOT correctly identified. This suggests that a portion of the negative feedback was due to students' misunderstandings, rather than issues with the tool's functionality. This is, indeed, one possible risk in the design of FEEDBOT: since the feedback is very limited, and relies upon the student to identify *where* in the identified step there is a mistake, it is possible that students will not understand the feedback that is given. This is obviously compounded by the fact that occasionally the tool was, indeed, wrong! But the same can be true of nearly any intervention, including traditional teaching assistants!

An additional 4% of the "Not Helpful" ratings were due to a bug caused by a misconfiguration of dependencies, which had to be configured before assignment release (see §3.4). We corrected those once we noticed, but any submissions that had already been processed included erroneous complaints by FEEDBOT about references to unbound identifiers. Removing those 41% reduces the total number of unhelpful comments to around 13%.

4.2 Qualitative Feedback

Around 30% of students gave feedback about the use of FEEDBOT alongside other general anonymous feedback for the course. Of those, 71% reported using FEEDBOT on most assignments, and over 90% used it at least once. Additionally, 83% of those that used it said the feedback was either very or sometimes helpful, and another 5% indicated that FEEDBOT always told them their code was fine, and they didn't get later deductions. This reinforces the notion that FEEDBOT has almost a 90% success rate.

In free response, many students complained about the rate limiting of the tool, which indirectly confirms utility. While the "cooldown" period was an addition mechanism to ensure that students still did independent work, the hard upper limit on the number of submissions was primarily for budgeting reasons. Both, however, were somewhat inflexible, as they did not allow the student to determine on which submissions they wanted feedback. We intend to change how this is done in the future, in order to have the rate limiting be enforced based on the submissions students view, rather than what they submit, which would alleviate many of the complaints (e.g., that by the time they had submitted something they wanted feedback on, they had used up all their submissions).

4.3 Future Work

Expanding Language Support While the FEEDBOT server is language agnostic, the FEEDBOT client has some language bias – in particular, it expects to be able to split assignments using particular comment tokens specific to Racket.

Conducting Studies: As an experience report, we clearly are only reporting on our experience with this tool. Among many potential things to study, it would be interesting to know the code changes that happened after viewing the responses, and to code those changes to see if they were connected to the feedback from FEEDBOT.

Enhancing User Experience: Addressing the rate limiting issue involves exploring alternative methods of managing FEEDBOT's usage without restricting access. While we plan on making a minor adjustment to shift where the rate limiting occurs (see §3.6), we could also imagine an adaptive feedback system that adjusts the frequency of feedback based on individual student performance, which would be an intervention aligned with equity.

5 Conclusion

In this experience report, we have described a new open source tool called FEEDBOT that can be used to provide formative feedback on open-ended programming assignments. It uses LLMs to provide structured, limited, but actionable feedback, addressing key challenges in large-class settings. We have shown that even in this restricted form, it can assist students.

Table 2: Effect of FEEDBOT Usage by Performance In Class

HW	Quartile 1 Scores (Usage)	Quartile 2 Scores (Usage)	Quartile 3 Scores (Usage)	Quartile 4 Scores (Usage)
HW6	65.5% → 80.0% (14%)	82.5% → 89.5% (30%)	87.6% → 91.2% (40%)	93.0% → 94.5% (46%)
HW7	70.5% → 79.5% (24%)	80.5% → 82.5% (53%)	86.3% → 88.4% (60%)	84.5% → 93.0% (69%)
HW8	73.5% → 76.4% (18%)	82.9% → 86.2% (41%)	88.8% → 94.4% (57%)	92.4% → 95.3% (59%)
HW9	88.6% → 88.1% (16%)	93.8% → 95.3% (33%)	96.6% → 97.1% (50%)	97.0% → 97.5% (54%)
HW10	84.4% → 90.3% (27%)	87.6% → 92.0% (49%)	90.7% → 94.4% (62%)	93.4% → 96.3% (68%)
HW11	72.7% → 86.0% (16%)	84.5% → 84.6% (43%)	87.4% → 93.0% (45%)	91.3% → 94.7% (54%)
HW12	62.3% → 71.7% (22%)	74.5% → 82.7% (38%)	76.9% → 82.2% (44%)	84.3% → 86.6% (51%)

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