Pomona: Continuous Code Quality Improvement via Small, Automated Changes at Bloomberg

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Abstract

In this short experience paper, we present Pomona, a lightweight agentic tool that utilises agent skills for continuous automated code quality improvement. Inspired by the philosophy of Kaizen™, Pomona automates a cycle of discovery and incremental repair: a Scanning skill identifies improvement tasks (e.g., linting violations, technical debt markers, and test gaps) and prioritises them in a structured backlog, while a Repair skill generates tiny pull requests (PRs) targeting ~10 lines of diff. This human-in-the-loop design enables frequent, low-risk improvements while maintaining engineer trust and productivity and reducing technical debt. We evaluated Pomona through a one-month deployment in a team and a questionnaire distributed to 10 senior engineers. Our preliminary results are promising: 15 of 17 generated PRs were successfully merged with a median time-to-close of under 2 hours. Furthermore, 8/10 of surveyed engineers expressed a desire to adopt Pomona, praising small diff sizes and Pomona's focus on improving code quality. We conclude by discussing actionable insights for researchers and practitioners on strategies for effective agentic deployment in industry.

Keywords

AI4SE, Agent Skills, Agentic AI, Software Quality, Technical Debt

1 Introduction

As Large Language Model (LLM) integrations and agentic solutions [13, 14, 16] mature in the domain of Software Engineering (SE), organisations are increasingly looking to implement reliable techniques to improve the software development process for their employees. Although some studies on the impact of LLM-based SE tools on developer productivity have reported significant increases in development speed [12], others have observed that developers using LLMs tend to perform their regular tasks more slowly than without (while believing they are working faster) [2]. Notably, He et al. [6] found that agent adoption in open source repositories increases development velocity only temporarily and comes at the cost of longer-term increases in code complexity and quality issues.

To reconcile this tension between short-term speed and long-term maintainability, we present a novel, Kaizen™-inspired agentic solution, dubbed Pomona, that utilises agent skills to improve code quality continuously through small, automated changes. Agent skills are user-defined instructions that enable autonomous agents to handle specialised, repeatable workflows [3, 11]. Pomona is composed of two such skills: one for identifying code quality improvement tasks and another for addressing them. It builds and maintains a structured, prioritised backlog of these tasks, which it gathers from multiple sources, e.g., static analysers, inline technical debt markers, test coverage gaps, and deviations from project-specific coding standards. Picking the highest-priority item from the backlog each time, Pomona generates tiny pull requests (PRs) targeting approximately 10 lines of diff, then updates the backlog and repeats the process. Pomona handles the needs and challenges of efficiently adopting AI by being ① low friction, in that this is a fully autonomous workflow that does not require engineers to adapt their development activities; ② low stakes, adopting a human-in-the-loop paradigm so that Pomona's contributions cannot affect the codebase without engineer review (with that process made especially simple given the size of Pomona's PRs); and ③ focused on improving code quality, ensuring that changes introduced by Pomona can only benefit the long-term maintainability of the targeted codebase.

Pomona has already been adopted by an engineering team at Bloomberg, with positive early impressions. To evaluate its potential value in practice, we conducted a preliminary mixed-methods study. Starting with a manual audit of 17 PRs generated by Pomona for the adopting team over the course of a one-month deployment, we observed both high acceptance and efficiency: 15/17 of the generated PRs were successfully merged, and 11 of those accepted required no human interaction beyond the mandatory review, all within a median time-to-close of less than 2 hours. We complement these findings with insights from a questionnaire distributed to 10 senior engineers. The results are promising, with 8/10 participants expressing a desire to try the tool, particularly valuing Pomona's small diff sizes (9/10) and focus on improving code quality (8/10).

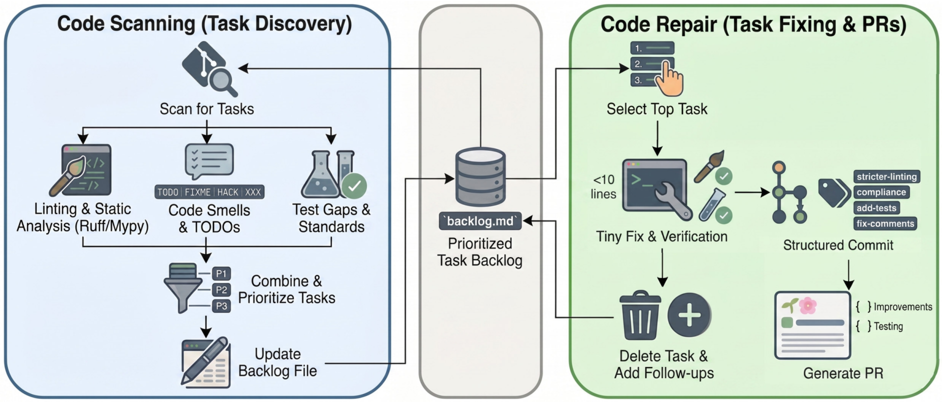

Figure 1: Overview of Pomona. Each shaded region represents the responsibilities of an agent skill (left: Scanning; right: Repair).

This short paper provides an in-depth description of Pomona's implementation and offers insights into practical strategies for deploying agentic AI4SE in a large-scale industrial environment.

2 Pomona Overview

Figure 1 illustrates an overview of Pomona, which comprises two agent skills: one for identifying code quality improvement tasks in the target repository and compiling them in a structured, prioritised backlog (the Scanning skill, §2.2); and another for selecting the highest-priority task in the backlog and generating a new PR that addresses it for human review (the Repair skill, §2.3). Leveraging the agent skills medium makes Pomona's implementation simple: the Repair skill, the Scanning skill, and the structured task backlog are each implemented as individual Markdown files that can be integrated with any current agentic product. This format also makes Pomona programming-language-agnostic (though our specific implementation, evaluated in §3.1, targets Python). The following sections describe each component and their cyclical combination to achieve a continuous code-quality improvement loop.

2.1 Prioritised Task Backlog

In Pomona, a structured backlog of code quality improvement tasks lies at the centre of the Scanning and Repair skills. The Scanning skill fills the backlog with prioritised improvement tasks, while the Repair skill consumes these tasks to generate new PRs with improvements for review. A backlog excerpt is shown in Figure 2.

Backlog improvement tasks are categorised in priority groups P1–P4 defined in the "benefit × ease-of-review" matrix in Table 1. By altering the specification of the Scanning skill, engineers adopting Pomona can define what constitutes *high benefit* in their development context. A good rule of thumb is that bug-catching improvements should always take priority over cosmetic ones. For example, a linting rule that prevents mutable default parameters is more valuable than one that reorders imports. For the specific implementation of Pomona we evaluated in §3.1, we included the following in our Scanning skill specification: "*high-benefit* changes catch real bugs or prevent future bugs (mutable defaults, loop variable capture, missing exception chains); reduce maintenance burden (removing dead code, fixing misleading comments); or improve developer experience (better error messages, clearer code)".

Following a similar process to the one described above, adopting engineers can also define what counts as *easy to review*. For our implementation, we included the following rule in our Scanning skill: "A change is easy to review if it is fully automated (auto-fix, formatting), mechanical and repetitive (reviewer can scan quickly), small in scope (single file or single rule) and does not introduce behavioural changes (pure refactoring)".

2.2 Scanning: Identifying Repair Tasks

The Scanning skill allows Pomona to automatically discover new code quality improvement tasks. It is executed as part of the Repair skill (§2.3), specifically when the backlog runs low on high-priority tasks (the P1 and P2 categories are empty). To refill the backlog, the Scanning skill initialises multiple sub-agents in parallel, each exploring a different discovery area. As described below, the quantity and purpose of sub-agents should be defined by the adopting engineer based on their needs. Once all sub-agents complete their searches, their outputs are combined into prioritised backlog tasks.

In our specific implementation of Pomona, three unique sub-agents are defined. Sub-agent 1 performs `ruff` rule expansions and `mypy` strict expansion. Sub-agent 2 searches the codebase for TODOs expressed as "`TODO|FIXME|HACK|XXX`", and classifies each finding according to the following guide: self-documenting removals (where the code is already done) are assigned as P1, clear fixes with obvious solutions are P1/P2, fixes requiring further domain investigation are P3, and aspirational comments are assigned in P4. Sub-agent 2 also searches for comments that contradict their surrounding code, as well as identifies dead code by searching for unused imports, commented-out code blocks (>3 consecutive commented lines), and unreachable code after early returns. Finally, sub-agent 3 identifies test coverage gaps by comparing source modules with unit test modules to reveal untested modules. It prioritises pure-logic modules without data dependencies (as these are easiest to test) and modules with complex branching logic (as these provide the highest value). In addition, sub-agent 3 checks compliance with the repository's defined coding standards (usually found in agent

Table 1: Priority Matrix for Task Management

	Easy to review	Hard to review
High benefit	**P1** — Do first	**P3** — Worth doing, plan the split
Low benefit	**P2** — Quick wins	**P4** — Parking lot (don't pick)

P1: High benefit, easy to review

- Remove unused `min_lead_in` / `min_lead_out` params from `lead_time_stat_timeseries_repos` + 2 callers
- Remove self-documenting TODOs in `utils/agg.py` (lines 35, 45)
- Enable ruff `I` (isort) incrementally — all auto-fixable
  - `core/` (11 modules, strictest-checked — start here)
  - `utils/`
  - `pdata/`
- Enable ruff `UP` (pyupgrade) for `core/` — most rules auto-fixable

Figure 2: Excerpt of Pomona's backlog for the adopting Bloomberg engineering team featured in §3.1.

configuration files) and looks for long functions (i.e., functions longer than 50 lines) that can be decomposed into smaller parts.

Once all agents complete their searches, the Scanning skill concludes by aggregating their findings. This aggregation is done in two steps: First, the findings are listed and concatenated, and duplicate findings are removed. Second, each unique finding is assigned to a priority category following the priority matrix shown in Table 1 and rules described in §2.1.

Now with priority levels assigned, tasks are converted to follow the backlog item format (shown in Figure 2) and added to their corresponding priority category. At this point, these tasks are ready to be addressed by the Repair skill, described in the following section.

2.3 Repair: Solving Tasks Identified by Scanning

The Repair skill is Pomona's point of entry, implemented as an agent skill intended to be either manually executed by an engineer or configured to trigger periodically (e.g., once per day).

The first step of the Repair skill instructs the agent to access the task backlog at the root of the target repository. If the backlog file does not exist or the high-priority (P1 and P2) task categories are empty, *the* Scanning *skill is executed first*, after which the agent returns to complete the remaining steps in the Repair skill.

When there are tasks in the backlog, the next step is to *select the first task from the highest-priority category*. If an item has sub-items (as in Figure 2), the instructions specify to select the first sub-item.

The next step is to *implement the fix*. For this, a few rules are defined. First, any changes should be validated with the project's testing and linting commands (as specified by the adopting team). Second, changes must be small: since the goal is to create tiny, easily-reviewable PRs, the agent should aim for roughly 10 lines of diff. If a change exceeds that, the agent is instructed to split it using a few strategies provided by the adopting team. For example, in our implementation, one such strategy is to enable linting rules/add tests for one directory at a time, and then add follow-up items for other directories to the backlog.

Once the code changes are made and validated, the agent *updates the backlog* by deleting the completed task and adding follow-up tasks (if any). Since the backlog is stored in the repository, there is no need to maintain a separate log of completed tasks, as the project's `git` history tracks changes made to the backlog over time.

With the code and backlog changes complete, the agent can now *commit the changes*, including a clear motivation for the change in the commit body and links to relevant resources to help human reviewers better understand these automated changes when reviewing the project's history down the line.

The final step of the Repair skill *asks the user whether they want to generate a PR*. If so, the agent creates one (our implementation uses Bloomberg's internal Model Context Protocol (MCP) integrations to achieve this) following the repository's standard PR template. This choice is optional depending on the control paradigm: if the skill is autonomously triggered periodically (e.g., once per day) rather than initialised by an engineer, this user choice is skipped, and a PR is created as soon as the previous steps are complete. The PR title is generated as a one-sentence summary of what was improved and why it matters, prefixed with specific emojis to clearly indicate that the PR is AI-generated. For the PR description, the agent is instructed to lead with the concrete outcomes for engineers. It only includes additional sections if they add value beyond the title. For example, it would include the "Improvements" section only if the title alone does not sufficiently explain the changes, and the "Testing & Linting" section only if special testing was done beyond the project's standard testing commands.

3 Early Insights and Evaluation

We conducted a mixed-methods evaluation comprising a manual analysis of PRs generated by Pomona for one team over a one-month adoption period and a questionnaire distributed to non-Pomona users gauging their interest in its concept.

3.1 Pomona Pull Requests

We assessed Pomona's early-stage impact by analysing the 17 closed (merged or rejected) PRs generated by Pomona at the time of writing. We manually extracted standardised metadata for each PR, including the resolved task's priority level (P1–P4) and nature (i.e. source). To measure the complexity of each PR, we recorded the diff size (files and lines of code) and whether the changes led to additional subtasks being added to the backlog. Finally, we observed the outcomes and review dynamics for each PR, including whether the PR was merged, the time between creation and closing, the number of reviews and non-review comments, and whether any follow-up commits were required by the reviewers before merging. For rejected PRs, we noted any explicit reasoning provided.

3.1.1 Results. Our evaluation period spans approximately one month from mid-March to mid-April 2026. The team preferred to retain full control over the volume of AI-generated PRs in their repository, so a team member manually executed the Repair skill for each new PR. The team aimed for a goal of "one Pomona PR per day", which they largely achieved, producing 17 PRs across 22 workdays. Across these PRs, we observed a strong overall acceptance rate of 88.2% (15/17).

Regarding backlog priority levels, all PRs generated by Pomona were P1. While tasks existed in the other priority-level groups, there were sufficient P1-level tasks such that the other priority groups weren't reached within the one-month evaluation period. The majority (14/17) of the PRs generated by Pomona addressed various `ruff` rule violations, and two other PRs addressed dead code in the form of removing unused function parameters. Notably, one PR was directly requested by a team member, who manually added the corresponding backlog entry in a different PR. This example highlights the flexibility offered by Pomona's accessible backlog in the repository root.

Both PR rejections were due to "race conditions" in which Pomona was executed twice before a human review, resulting in duplicate PRs. In both instances, the duplicate was rejected, while the original was accepted. Taking this oversight into account, we revised Pomona to skip tasks already addressed by open PRs.

Of the 15 accepted pull requests, none required additional human commits, and 11 were accepted with no comments or interactions beyond the mandatory human review before merging, suggesting that the scope of tasks tackled by Pomona was small enough to warrant only a brief review. Reflecting this low complexity, the median time to close (either merge or reject) Pomona PRs was only 1 hour and 43 minutes, with more than 70% (12/17) of PRs closed within 4 hours of creation. We observe outliers at both ends of the time-to-close measurements, ranging from a minimum of 1 minute (when duplicate PRs were immediately closed) to a maximum of just under 75 hours (when the team did not have a chance to close a PR before the weekend). Regardless, we observe that almost three-quarters of PRs were handled on the same business day they were created, supporting the claim that Pomona is low-friction and integrates into existing workflows without significant cognitive overhead.

Pomona PRs also exhibited a substantial range in size. All PR size metrics (files/lines changed) exclude backlog changes to focus solely on codebase impact. The median number of files changed was 4 (mean 4.8), with a minimum of 1 and a maximum of 17. One potential cause for concern was the number of lines changed, calculated as the sum of added and deleted lines. Here, the median was 16, the mean was 29.4, and the values ranged from 5 to 139. However, even for the largest PR, the team reviewed and merged it in just over an hour, indicating that even larger-scale PRs can be manageable when the targeted improvements are intuitive.

Finally, three of the accepted Pomona PRs added new tasks to the backlog, including one that triggered the `Scanning` skill, which added 8 new tasks. The other two PRs added sub-tasks directly related to the task at hand to ensure the scope of changes did not become too large to review easily.

3.2 User Study

To gauge interest in Pomona's concept, we created a questionnaire to distribute among engineers. We specifically targeted engineers in Bloomberg's Developer Experience (DevX) teams, given their rich understanding of the organisation's development tooling. The questionnaire contained 12 questions, the first five of which covered participant demographics, including job title, years of experience, and familiarity with AI4SE tools. Next, the questionnaire presented the participant with Figure 1 alongside a high-level description of Pomona, followed by seven questions concerning whether the tool seems useful (and if not, why), how many pull requests the participant would be willing to review per week if they adopted the tool, which features seem most valuable, what types of tasks they would want Pomona to tackle, and concluding with an opportunity to provide any additional feedback to refine the concept. We provide the questionnaire as part of our supplementary materials [15].

3.2.1 Results. In total, 10 participants completed the questionnaire. This cohort comprised two Team Leads and eight Senior Software Engineers, of whom six had more than 10 years of experience, while the remaining four had 4–10 years of experience. In terms of experience with AI-assisted software development (i.e., in-IDE tools), seven stated they use these tools daily, one weekly, another monthly, and one never. Similarly, five participants stated they interact with agentic SE tools (e.g., fully automated PR generation, code review) daily, one weekly, two monthly, and one never.

When presented with Pomona's concept, the majority (7/10) of participants felt the tool would be useful, and more (8/10) stated they wanted to try Pomona in future. If they adopted Pomona, most participants (7/10) would be willing to review 2–3 PRs per week, which corresponds to the patterns observed in the adopting team described in §3.1. The remaining responses were split: one participant was willing to review more than 5 PRs per week, while two others preferred 1 or fewer. When asked about the most appealing features to them among those described in the concept, 9/10 highlighted small diffs, while 8/10 highlighted the focus on improving code quality. Half chose the automated identification and completion of tasks, suggesting they appreciate Pomona's format but require high confidence and control over the automated task selection and prioritisation process.

In terms of tasks the participants wish Pomona would tackle, six requested handling of TODOs/outdated comments, four mentioned static analysis/linting issues, three mentioned simple bug fixing, and another three mentioned dependency management, seemingly because they trust agents to handle issues of that scope autonomously. Other suggestions included documentation, adding tests (which would be the "*one exception to the size [limit] of the PR*"), performance fixes, and removing dead code.

A few participants also highlighted potential drawbacks and areas for future improvement. They highlighted the risk of review overload, fearing that Pomona might simply "*create more open PRs for actual humans to handle*", or generate "*gratuitous churn*" by addressing tasks that, while technically valid, are "*not relevant enough to care about*". Another participant noted that "*sometimes code smells require large-scale refactoring which seems to be out of scope [for Pomona]*". However, the fact that 8/10 participants still expressed a desire to try the tool suggests that, for many, the aforementioned code quality improvement tasks may be smaller in scale but are primarily neglected due to a lack of engineering bandwidth rather than a lack of perceived value. In other responses, trust and agency emerged as significant topics of interest. Several participants were wary of "*trust[ing] the AI judgement to discover the right issues to fix*" and expressing a preference for a user-controlled paradigm (i.e., a fully user-triggered `Repair` skill, as described in §3.1) over an autonomous triggering system, with this desire also extending to want "*control over what gets prioritised first*". Finally, one respondent requested the ability for Pomona to iterate upon its own PRs based on reviewer feedback. We consider iterative agentic PR refinement a promising area for future work.

4 Discussion

Based on our early experiences in deploying and evaluating Pomona at Bloomberg, we discuss actionable insights into industrial agentic AI adoption and future work for both researchers and practitioners.

Small Changes Facilitate Adoption. Pomona's early success was not in solving the most "difficult" coding problems, but in solving high-priority, low-complexity tasks with high accuracy and minimal friction. The high PR acceptance rate in our preliminary real-world deployment suggests that current agents can confidently tackle "low-hanging fruit" in software repositories (e.g., linting violations, dead code). Small, intuitive changes reduce both reviewer scepticism and cognitive load. In fact, despite Pomona's strong performance, the adopting team intentionally limited its output to at most 1 PR per day, indicating that human review bandwidth is a far greater bottleneck in AI-driven development than code-generation speed. Moreover, 90% of participants cited small diffs as Pomona's most appealing feature, highlighting the importance of code reviewability in accepting AI contributions.

AI for Technical Debt Management. Our findings suggest that engineers want AI to handle "neglected" tasks (TODOs, outdated comments, dead code, and linting) because while these tasks are important, engineers struggle to find time to address them manually. Pomona demonstrates that agents can easily be configured to target TODOs, outdated comments, and dependency updates. These are the specific areas where engineers feel a strong "value-to-effort" gain from automation. The fact that several Pomona PRs either generated further tasks also shows that AI can act as a catalyst for ongoing technical debt management rather than just a one-off tool.

Prioritisation is as Important as Detection. While static analysis tools can identify many potential tasks, selecting the right improvements to apply is crucial. Our benefit × effort prioritisation strategy (Table 1, §2.1) can focus agents on high-benefit, low-friction changes, ensuring that automated changes deliver tangible value.

Expert Scepticism and Human-in-the-Loop. Through Pomona's PR-driven format, engineers retain full control over whether any changes are integrated into the codebase. These PRs clearly communicate the purpose and impact of each modification, following consistent templates that prioritise clarity and benefit for the engineer. This transparency is critical for building trust in automated changes. Our survey reveals that experienced engineers (10+ years' experience) remain wary of "agentic judgment" in prioritising tasks. As a result, current agentic solutions should continue to promote a human-in-the-loop paradigm (such as that of Pomona, with its user-initiated workflow and accessible backlog), while a potential avenue for future research could be in automated relevance filtering. Developing techniques that can distinguish "relevant" code changes from merely "valid" ones is a high-priority frontier.

Agentic Task Decomposition. Another relevant direction for future research to facilitate industry AI adoption would be to investigate how agents can reliably identify and break down large tasks into small, easily reviewable ones without human intervention.

Quantifying Cognitive Load. Currently, it is difficult to identify the threshold at which agentic PRs transition from helpful suggestions to "gratuitous churn". Future research should shift from binary "merge/reject" rates toward multi-dimensional metrics (including subjective engineer perceptions) that capture the cognitive load of human-AI collaboration. This effort requires devising proxies to measure the context-switching cost of reviewing both AI-generated and human-authored code, as well as the mental effort required to verify various types of automated changes.

5 Related Work

Preliminary research on agent skills in different domains has explored their effectiveness in improving task performance, including SE tasks [5, 7], and how to organise [8], secure [9, 10], and evolve skills at scale [1, 4]. The results generally show that curated skills can improve performance [7], especially in specific scenarios [5], although the gains in SE tasks remain context-dependent [7] and their overall impact is still unclear[5]. These results highlight the challenges of designing effective, reusable procedural knowledge for SE tasks, and the need for governance and validation mechanisms when deploying such skills in practice [9, 10].

In contrast to previous work, which primarily focuses on evaluating, generating, or securing agent skills, our work investigates how agent skills can be devised and integrated in a real-world industrial setting based on user needs. The skills we present enable low-friction, continuous, incremental code-quality improvement, and we highlight its value to users through a preliminary study. In addition, we report practical lessons from its deployment.

6 Conclusion

This work introduces Pomona, an agentic tool that leverages agent skills for continuous code quality improvement through automated, easily reviewable changes. Our preliminary evaluation, including a one-month team deployment and a senior engineer questionnaire, demonstrates Pomona's potential to help manage technical debt with minimal impact on development velocity, and to serve as a low-stakes, high-benefit approach to agentic AI adoption in SE.

Data Availability Statement

As Pomona has been developed within Bloomberg's internal systems and repositories, data and source code are not publicly accessible. However, the entire implementation of Pomona consists of only three Markdown files (the `Repair` skill, the `Scanning` skill, and the backlog) and can be combined with any current agentic product. In this work, we have explained in detail how to implement such a tool in practice, enabling academics and practitioners alike to adopt it in future. Moreover, we make the questionnaire we distributed for user evaluation available [15].

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