AI-Assisted HCI Design and Sprint Cadence in Scrum Software Development

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Abstract

This article explores how AI-assisted prototyping impacts the cadence of Scrum software development sprints. Through a qualitative pilot study across ten case studies (cross-sector organizations), we observed that integrating AI-assisted generative co-design tools into Scrum teams significantly shortened sprint feedback loops, enabling UX designers and product owners to rapidly generate and refine prototypes. However, AI's inherent opacity introduced process debt, potentially slowing down later iterations. To address these challenges, we propose two practical guidelines: adding a "model state" checkpoint to daily meetings and including explainability criteria in the Scrum definition of done. Our findings underscore the critical balance between speed gains and the need for transparency and user trust in AI-assisted human-computer interaction (HCI) design. This study serves as a precursor to further extended research in this area.

Keywords: Scrum software development; scrum HCI; human–AI collaboration; HCI; AI-assisted HCI

1. Introduction

Software organisations are profressively incorporating artificial-intelligence (AI) components info both product functionality and design workflows. While AI can personalize interactions and automate routine HCI tasks, its opaque decision processes have the potential to erode user trust [11]. To date, there has been a paucity of empirical research examining the impact of AI-assisted prototyping on the fast, time-boxed cadence that defines Scrum. The central inquiry of this study is:

RQ: How does AI-assisted prototyping change sprint cadence in Scrum teams?

From a Lean & Agile software-development (LASD) perspective, AI-enhanced HCI design appears to be a logical progression towards the optimisation of feedback loops [8]. In ten cross-sector organisations (finance, health-tech, e-commerce), Scrum teams were observed in our pilot study of 10 case studies to embed generative-AI co-design tools into two-week sprints. Designers and product owners were able to produce high-fidelity mock-ups within hours, demonstrate them in sprint reviews, and capture user feedback before the next planning session [12]. These gains are consistent with Scrum's emphasis on flow efficiency and "working software over comprehensive documentation" [13]. However, the opacity of deep-learning models introduces new forms of process debt that have the potential to undermine later iterations if not managed effectively.

The present paper is of twofold significance: (1) The following argument is put forward to demonstrate the existence of qualitative indications that AI-assisted prototyping can compress sprint feedback loops in Scrum teams. (2) The proposal sets out two pilot-ready practices that are designed to ensure transparency while maintaining pace. The first of these is the addition of a model health checkpoint to daily stand-ups, and the second is the extension of the Definition of Done (DoD) with the inclusion of explainability criteria.

2. AI-Driven HCI Design in the context of Scrum

Recent ISD research has examined best practices in AI-enhanced software workflows [3], debt detection in agile processes [4], and the challenges of remote collaboration in agile teams [3]. Integration AI in HCI design has attracted growing interest, particularly for enhancing user experience through personalisation, automation, and co-creative tasks [7], [14,15]. Human-AI collaboration combines human intuition with AI's data-driven analysis to support creative and decision-making activities [10]. This collaboration is prominent in areas like content creation, educational dialogues [9], and emotional support systems, where AI augments human roles rather than replacing them. Challenges persist in achieving transparency and trust in AI systems, e.g.: how AI reaches conclusions, which impacts trust and engagement [2]. Potential of AI to enhance user experiences through personalisation, automation, and creative collaboration is widely acknowledged [6]. Research highlights the need for personalised, comprehensible AI explanations and transparency mechanisms that support user control [5,6]. Ethical concerns, such as bias and inclusivity, further complicate AI deployment in HCI systems [5]. The role of AI in HCI systems has become increasingly significant, particularly in its capacity to personalise experiences, automate complex tasks and foster creativity [7]. The deployment of generative AI tools demonstrates the ability of AI to enhance iterative design processes through the expeditious prototyping and generation of creative outputs and workflows [7], [15,16]. The utilisation of AI-driven tools may significantly reduce the time and manual effort required. While there is a general consensus that AI can enhance productivity and creativity, concerns persist regarding the current limitations of these systems, particularly in terms of user control and the ability to refine AI-generated outputs.

Despite the growing interest in AI in agile, it is still unclear how exactly it affects sprint economics and process debt. The dynamics roles of UX designers, developers, and Product Owners (POs) in co-creating with AI are poorly described, and there is little evidence of such practices across industries, which requires further multi-study research.

3. Method

A qualitative research methodology was employed, focusing on pilot case studies to preliminary explore the integration and impact of AI in HCI design, particularly in the context of Human-AI collaboration. The objective was to elucidate how AI technologies can influence user experience and system design within diverse industry contexts, providing a foundational understanding pertinent to the research questions. Case study method was chosen due to its efficacy in exploring complex phenomena within their real-life contexts. This method facilitated an in-depth examination of how various industries incorporate AI into their HCI systems. Ten companies were selected for the pilot study, reflecting a range of industries that employ AI in HCI systems. The selection was guided by the following criteria:

1. AI Utilization in Design: Companies that integrate AI as a central component of their HCI systems were selected.
2. Human-AI Collaboration: A preference was given to organizations that showcase innovative. Allowing for an analysis of user influence over AI-driven outcomes.
3. Diversity of Industries: Including a broad spectrum of sectors ensured the coverage of a wide range of AI applications and user interactions, enhancing the generalizability of the findings.

These cases were selected not only for their innovative use AI in HCI design, but also because they applied Scrum delivery cycles and sprint-based development. Observations and interviews were aligned with sprint cadences, allowing researchers to capture fast feedback, evolving team practices, and AI usage during iterative planning and retrospectives. All ten organizations use Scrum: eight use Scrum, and two adopt a hybrid Kanban-Scrum workflow. Each team works in fixed two-week sprints and releases a potentially shippable increment at least once every four weeks. Case studies were purposefully selected on this basis because the stable sprint cadence and clear artifacts (backlogs, sprint reviews, velocity charts) provide a consistent window into how AI-assisted HCI design activities impact flow performance. Data collection therefore spanned two full sprint cycles per team (4 weeks), including sprint planning, daily meetings, reviews, and retrospectives. This design allows us to attribute observed time-to-lead reductions and quality changes directly to the integration AI co-design tools into a Scrum cadence.

Data was collected through a combination of semi-structured interviews, document analysis, and observational studies:

(1) Interviews: Conducted with key stakeholders, including UX designers, developers, POs and end users, to gather diverse perspectives on AI integration in HCI. 30 interviews were held, focusing on understanding the role of AI in system functionality, the strategies for ensuring transparency, and the ethical considerations involved in design [9].

(2) Observations: Observational studies were conducted to witness the real-time use of AI in HCI, providing insights into the practical implementation Human-AI collaboration and its impact on user engagement and decision-making.

(3) Document Analysis: Internal documents such as design guidelines and project reports were reviewed to understand the structured approaches and guidelines followed by companies regarding AI integration.

Using thematic analysis, key patterns and themes across the case studies were identified, particularly focusing on the integration of AI, the effectiveness of Human-AI collaboration, and challenges such as transparency and trust. Cross-case analysis helped in highlighting commonalities and differences in AI integration approaches across different industries.

4. Findings of pilot case studies and discussion

Evaluation of these AI-enabled HCI systems reveals several key themes: (1) AI prototypes helped shorten sprint feedback cycles, (2) improved DoD clarity, and (3) enhanced cross-role collaboration.

AI-supported decision tools enabled real-time analytics in finance, reducing lead time for key decisions. A healthcare company utilising AI-driven recommendation engines observed an increase in patient satisfaction when treatment plans were tailored to individual preferences. This finding is consistent with the results reported by Rae, which indicated that the use of personalised AI systems was associated with increased user engagement [9]. Furthermore, systems that permitted user input and modification exhibited heightened engagement, as evidenced by a marketing company where users could override AI-generated suggestions, which is consistent with the collaborative model [14].

There was a strong correlation between user trust in AI systems and the level of transparency and user control afforded to them. It was observed that users demonstrated greater trust in systems when they were able to comprehend the rationale behind the AI's decision-making process and intervene when necessary. E.g. a recruitment company that provided explanations for AI-driven candidate rankings observed an increase in the level of trust among hiring managers, a finding that is consistent with the findings [15]. A content generation company discovered that users placed a high value on the capacity to engage in co-creation with AI, which served to enhance their sense of control and confidence in the system. This finding is consistent with the results of the study [2]. Conversely, a deficiency in user control over AI systems was found to result in a decline in trust, as observed by a retail company utilising AI for inventory management.

Answers to the research question:

- AI customer-service tools enhanced engagement through faster, more tailored responses, but transparency issues persisted.
- AI-supported tools reduced sprint feedback time (e.g., AI-assisted prototyping completed within a day instead of a week).
- User control over AI outputs aligned with Scrum DoD criteria.
- Real-time feedback mechanisms improved sprint retrospectives and backlog grooming.
- Transparency of AI recommendations improved trust and accelerated team decisions.
- Co-creation capabilities allowed roles like UX designers and developers to iterate jointly with AI support.

In summary, the results of this pilot study, show that there can be a significant impact of AI on HCI design. The research results outlined ways in which AI-based systems increase personalization, scalability, and automation, and also explained key challenges related to transparency, trust, and ethical concerns. Our results show that AI-assisted HCI design likely does more than speed up prototyping by, among other things, transforming the roles, ceremonies, and artifacts embedded in Scrum Software Development. (1) role boundaries are blurred, (2) UX designers become temporary engineers, while POs act as model stewards who arbitrate between speed and model risk trade-offs. (3) Teams therefore need an explicit "AI governance" mandate in their DoD to prevent silent accumulation of process debt. (4) ceremonies require lightweight AI checkpoints. During sprint planning, teams should estimate not only story points but also the explainability effort of the model. (5) During daily standups, a quick "green/red model flag" round reveals drifting accuracy early on. (6) Sprint reviews benefit from live demonstrations of explainability, allowing stakeholders to see what the model "thinks" rather than just what it predicts. (7) Transparency dashboards act as Lean waste detectors. By revealing wait states (e.g., data labeling bottlenecks) and mispredictions in near real time, dashboards fulfill the Lean imperative to make waste visible. Taken together, these observations extend prior LASD work by pointing out specific artifacts and touchpoints where AI enhances, rather than hinders, agility. They also nuance the claim that GenAI Tools always enhances velocity: if teams fail to build in explainability and DoD safeguards, they incur hidden rework that only becomes apparent after a few sprints. Future research should examine how such safeguards scale across large, distributed programs and regulated domains.

5. Future research

Future work should explore how these practices scale in remote or regulated environments and develop industry-specific frameworks for explainable, fair AI. It is possible that different industries may require models that are tailored to their specific needs, thereby providing an opportunity for further exploration in the field of HCI. Secondly, the explainability of complex AI models, such as deep learning and neural networks, remains a significant challenge. Further research into explainable AI (XAI), as discussed by Schoeffer et al. (2024), should aim to enhance the accessibility of these models without compromising their technical depth [10]. Future studies should investigate the potential for integrating XAI into everyday HCI systems, with a view to fostering greater user trust. Finally, ongoing research is needed on the ethical and fairness aspects of AI systems.

Researchers should explore how ethical frameworks can be embedded in AI design, in line with the issues raised in Agnew et al. (2024), to address systemic bias and develop more inclusive AI systems [1]. The insights derived from this research are not only pertinent to the companies under examination but also have broader implications for companies across a range of industries that are integrating AI into their systems.

Lessons learned from these pilot case studies will inform more qualitative and empirical research that can be used to develop AI systems that prioritize user trust, facilitate ethical and transparent interactions, and enable users to retain control over AI decisions.

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