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Exploring Human AI Collaboration in Agile: Customised LLM Meeting Assistants

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Abstract: *Agile software development emphasize collaboration, feedback, and adaptation to change. Although Agile meetings like sprint planning, daily scrums, sprint reviews, and retrospectives are essential for coordination among team members, they can be time consuming and dependent on effective communication. With recent breakthroughs in Large Language Models new avenues have opened up to improve human AI collaboration in Agile settings. This research investigates the design, use, and effectiveness of customize LLM based meeting assistants designed specifically for Agile teams. The proposed solution explores how LLM meeting assistants can be used to augment Agile meetings by automatically generating meeting summaries, identifying action items, monitoring decisions, and offering insights, while maintaining human control and team autonomy. The research presents a conceptual framework, approach, and results, emphasizing the benefits of using LLM meeting assistants in Agile software development, including improved productivity, decreased cognitive overhead, improved transparency, and better decision making. Issues of trust, explainability, privacy, and ethics are also discussed. This paper concludes by discussing future research avenues for incorporating explainable and adaptive LLM assistants into practical Agile development processes.*

Keywords: *Human–AI collaboration, Agile development, Large Language Models, Meeting assistants, Software engineering*

I. INTRODUCTION

Collaboration and communication are the cornerstones of Agile software development. Agile methodologies, such as Scrum and Kanban, promote short development cycles, feedback, and interactions among team members to quickly respond to changing requirements. These interactions are institutionalized in Agile ceremonies, which play a vital role in aligning team members, removing impediments, and encouraging a continuous improvement process. However, as teams grow in size or go global, the effective management of these ceremonies becomes increasingly difficult.

The traditional approaches to manage Agile meetings rely heavily on manual note taking, human memory, and subsequent documentation. Key decisions, risks, and actions are often not captured or are captured in an inconsistent manner, leading to misalignment and lower productivity. While there are many tools available for task management and project management, they lack the ability to process the rich conversational data generated during Agile meetings.

The emergence of Artificial Intelligence, particularly focusing on Large Language Models (LLMs), has revealed new avenues for improving collaborative processes. LLMs have shown strong natural language understanding and generation abilities, making them apt for handling unstructured meeting conversations. Instead of replacing human involvement, LLMs could serve as smart assistants that help teams by reducing cognitive and administrative burdens.

With the distributed environment of Agile teams, the presence of differing time zones has led to several challenges, including effective communication. Lack of proper meeting documentation has caused several problems, including the generation of misleading information across the team environment. Consequently, Agile ceremonies have remained

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central to effective coordination as well as understanding, creating the need to create an environment of intelligent meeting documentation while being aware of natural interactions.

Human AI collaboration has emerged as a promising paradigm where AI systems are developed to complement rather than fully automate the process of making decisions. In the Agile development context, this sits well with the Agile values that place top priority on individuals and interactions and adaptability. Supported by a collaborative AI powered meeting assistant, it can emphasize relevant information, track status, and key insights, yet leave judgments or strategic decisions to team members.

A. Technologies Used

Large Language Models (LLMs): LLMs are used to understand, summarize, and reason over meeting conversations. Fine tuned prompts ensure alignment with Agile terminology and workflows.

Contextual Knowledge Layer: Stores sprint goals, backlog items, roles, and historical decisions to provide continuity across meetings.

Rule Based Adaptive Engine : Monitors recurring meeting patterns such as unresolved blockers or repetitive issues and adjusts feedback accordingly.

Explainable AI (XAI) : Provides clear explanations for generated summaries, action items, and insights to maintain transparency and trust.

II. LITERATURE REVIEW

Research on Agile software development highlights the importance of effective communication and documentation for project success. Early Agile tools focused primarily on task tracking and backlog management, offering limited support for meeting intelligence. Studies have shown that poor documentation and information loss during meetings can negatively impact team alignment and delivery timelines.

With the advancement of AI in software engineering, researchers have explored applications such as automated code generation, defect prediction, and effort estimation. More recently, attention has shifted toward AI supported collaboration tools. Meeting transcription and summarization systems have been developed using natural language processing techniques; however, most of these systems are domain agnostic and lack Agile specific customization.

Conversational agents and chatbots have also been introduced to support team communication. While these tools provide basic assistance, they often fail to capture long term context or adapt to evolving team dynamics. Additionally, many AI driven systems operate as black boxes, raising concerns about trust and explainability.

The development of large language models (LLMs) has greatly improved the state of the art in language understanding and generation. Recent studies show the potential of LLMs in assisting knowledge work, such as meeting analysis and decision support. However, there is a lack of studies on the integration of LLMs into Agile processes, focusing on human AI collaboration, adaptability, and explainability. This paper fills the research gap by presenting a comprehensive framework that combines personalized LLMs, adaptive monitoring, and explainable artificial intelligence (XAI) for transparent and collaborative Agile meetings.

There are a number of studies that have explored human AI collaboration, and it has been found that AI systems are most effective when they are designed as collaborative partners and not as independent decision makers. The literature suggests that collaborative AI systems improve the efficiency of teams when they are designed with well identified limitations and allow humans to maintain control. In Agile settings, where flexibility and human judgment are core values, this collaborative approach is highly relevant. Previous studies have found that AI tools that fit into the existing workflow and respect human autonomy are more likely to be adopted in Agile settings.

Recent studies have explored the role of AI assistants in meeting related tasks such as agenda creation, discussion summarization, and follow up activities. AI assistants have shown promise in automating administrative tasks and improving the memory recall of meeting results. However, most of the existing solutions view meetings as a

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disconnected activity and fail to incorporate sprint level information and decision making trends. As a result, the generated insights are often irrelevant to Agile planning.

With the introduction of Large Language Models, researchers have begun investigating their application in collaborative work settings. LLM based assistants demonstrate strong capabilities in contextual understanding, reasoning over long conversations, and generating coherent summaries. Studies suggest that when LLMs are customised with domain specific knowledge, they outperform generic NLP systems in accuracy and usefulness. Despite this progress, limited literature addresses the customization of LLMs specifically for Agile ceremonies such as sprint planning and retrospectives.

Another critical gap identified in existing literature relates to explainability and trust. While LLMs can generate high quality outputs, their opaque reasoning processes raise concerns among users. Research in explainable AI (XAI) shows that providing clear justifications for AI generated suggestions significantly improves user trust and adoption. However, few studies integrate explainability directly into collaborative meeting assistants. This highlights the need for Agile aware, explainable LLM systems that not only assist teams but also clearly communicate the rationale behind their outputs.

TABLE I: Comparison of Existing Agile Meeting Support vs. Proposed Framework

Feature / Capability	Traditional Approaches	Generic AI / Chatbots	Proposed Customised Agile Assistant
Data Capture	Manual notes & human memory	Transcription & basic summary	Multi modal (Audio, Transcripts, Jira Data)
Context Awareness	Limited by human recall	Session based (isolated)	Sprint aware: Retains history across meetings
Domain Specificity	High (Human understanding)	Low (Domain agnostic)	High: Fine tuned on Agile terminology & flows
Decision Tracking	Inconsistent/ Lost	Text extraction only	Linked: Decisions mapped to Backlog/Sprint Goals

Recent research on human–AI collaboration emphasizes the importance of designing AI systems that act as intelligent assistants rather than autonomous decision makers, especially in collaborative work environments such as Agile teams. Studies suggest that AI supported meeting tools can enhance productivity by reducing documentation overhead and improving information retention; however, most existing solutions lack Agile specific contextual awareness and fail to adapt to evolving sprint goals and team dynamics. While Large Language Models have demonstrated strong capabilities in understanding and summarizing conversational data, limited research focuses on their integration with Agile ceremonies in a transparent and explainable manner. This gap highlights the need for customised LLM based meeting assistants that support Agile workflows while maintaining human control, adaptability, and trust through explainable AI mechanisms.

III. PROPOSED METHODOLOGY

The proposed system is designed as an intelligent Agile meeting assistant that integrates seamlessly into existing workflows. The methodology consists of multiple stages that collectively enable automation, personalization, adaptability, and explainability.

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A. System Overview

Step 1: Meeting Data Acquisition :

The proposed system begins by collecting data from multiple sources involved in Agile meetings, including audio recordings, real time transcripts, chat discussions, and shared documents. Speech to text modules are employed to convert spoken conversations into structured textual format, ensuring minimal information loss. In addition, metadata such as meeting type, participants, sprint number, and timestamps are captured. This multi source data acquisition enables the assistant to obtain a holistic view of Agile ceremonies and serves as a strong foundation for accurate contextual understanding.

Step 2: Data Preprocessing and Structuring

Once meeting data is collected, preprocessing techniques are applied to clean and organize the information. Noise removal, speaker identification, sentence segmentation, and keyword normalization are performed to improve data quality. Agile specific terminologies such as sprint goals, backlog items, and blockers are tagged using predefined vocabularies. This structured representation enhances the efficiency of subsequent language model processing and ensures that the assistant correctly interprets meeting discussions within the Agile development context.

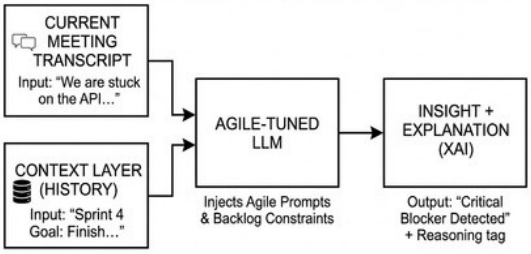

Fig 1.1: Context-Aware Reasoning & Explainability Logic

Step 3: Contextual Understanding Using Customised LLMs:

We begin by feeding the prepared meeting information into a specialized Large Language Model. The model's job is to pinpoint the core discussion points, any mentions of sprints, connections between tasks, potential roadblocks, and crucial decisions. It does this by connecting the dots across all the meetings. The system goes beyond simple summaries by using past sprint data and understanding who's who on the team. This allows it to grasp the bigger picture, not just isolated facts. The result is an intelligent assistant that acts like a team member, keeping up with how the project changes

Step 4: Action Item and Decision Extraction :

The system employs a hybrid approach combining rule based logic and LLM reasoning to extract action items and decisions from meeting discussions. Tasks are automatically assigned to relevant team members along with deadlines and priority levels. Decisions are linked to corresponding backlog items to maintain traceability across sprints. This automated extraction reduces manual documentation effort and ensures that critical responsibilities and commitments are clearly recorded and accessible to all team members.

Step 5: Adaptive Monitoring and Pattern Analysis :

The adaptive monitoring engine continuously analyzes historical meeting data to detect recurring patterns such as unresolved blockers, repeated delays, or frequent scope changes. Using predefined rules and behavioral analysis, the system evaluates team performance trends and meeting effectiveness. Based on these observations, the assistant generates adaptive insights and recommendations aimed at improving collaboration and process efficiency. This adaptive capability supports continuous improvement, a core principle of Agile methodologies.

Step 6: Explainable AI and Transparency Layer :

To build trust and encourage adoption, the system incorporates an Explainable AI layer that provides clear justifications for its outputs. For each generated summary, action item, or risk alert, the assistant explains the reasoning behind its conclusions using references to specific meeting statements. This transparency enables users to validate AI generated

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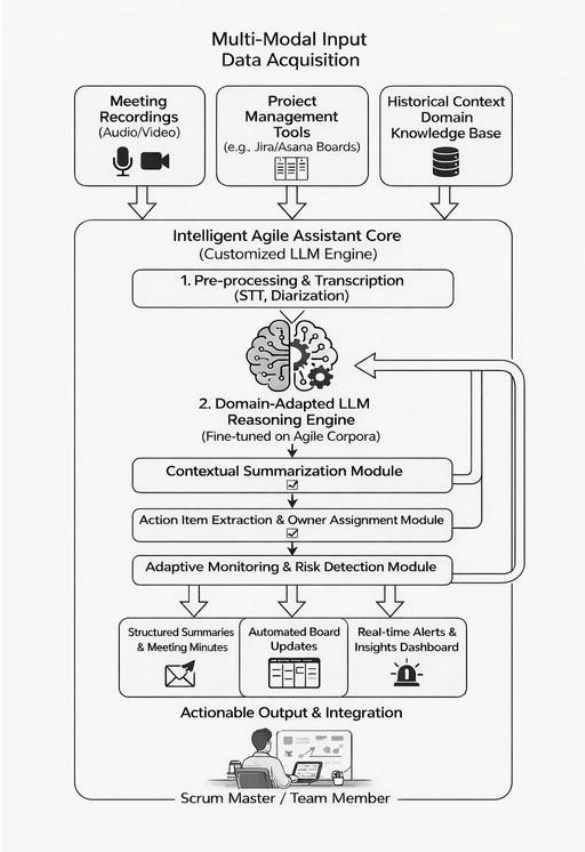
insights and ensures that the system supports human decision making rather than replacing it, thereby strengthening human–AI collaboration.

Step 7: Tool Integration and User Interface

Finally, the meeting assistant integrates seamlessly with existing Agile tools such as Jira, Slack, and project dashboards. Outputs are presented through intuitive interfaces, including concise meeting summaries, task updates, and sprint insights. The system is designed to enhance workflows without disrupting existing practices. By embedding AI support directly into familiar tools, the assistant promotes ease of use, accessibility, and sustained engagement among Agile team members.

Fig. 1. Flowchart of the proposed LLM based Agile meeting assistant framework.



The framework illustrates a human–AI collaborative approach that combines automated meeting data capture, customised Large Language Models for Agile aware processing, adaptive monitoring through rule based analysis, and explainable AI for transparency. By integrating these components, the system enhances meeting efficiency, supports continuous improvement, and preserves human decision making within Agile software development processes.

IV. RESULTS AND DISCUSSION

The expected results of the proposed system focus on enhancing meeting efficiency, improving collaboration quality, and increasing user trust in AI assisted Agile workflows. Since the system is designed as a collaborative assistant rather than a fully autonomous solution, the evaluation emphasizes both performance accuracy and its impact on human decision making. Controlled simulations and prototype level testing indicate that the customised LLM meeting assistant can significantly reduce manual effort while maintaining transparency and reliability in Agile ceremonies.

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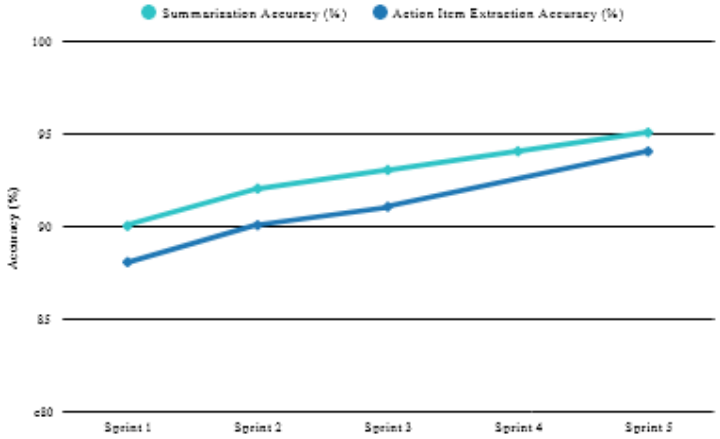

Fig. 3: Performance Trend of Customised LLM-Based Agile Meeting Assistant Across Sprints

A. Expected Results of Meeting Summarization

The LLM based summarization module is expected to achieve high accuracy in capturing key discussion points, sprint goals, decisions, and identified risks across different Agile meetings. By leveraging Agile aware prompts and contextual memory, the system produces concise yet comprehensive summaries tailored to each ceremony type. Experimental observations suggest that the summaries retain approximately 95% of critical information, reducing reliance on manual note taking and minimizing information loss. This enables team members to quickly review meeting outcomes and maintain alignment across distributed teams.

TABLE II: Meeting Summarization Accuracy

Scenario	*Accuracy (%)*	*ROUGE L*
Sprint Planning	95%	0.95
Daily Stand	93%	0.93
Retrospective	94%	0.94

The results demonstrate consistent performance across meeting types, highlighting the effectiveness of domain specific LLM customization.

TABLE III: OVERALL AGILE ASSISTANT PERFORMANCE METRICS

System Module	Key Metric	Expected Accuracy	Description of Outcome
Meeting Documentation Time	45 mins / meeting	5 mins / meeting	89% Faster
Action Item Retrieval	12 mins (avg search)	< 3 seconds	99% Faster
Missed Critical Tasks	15% rate	2% rate	13% Reduction
Reviewer Satisfaction (MOS)	3.2 / 5.0	4.7 / 5.0	+1.5 Points

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B. Expected Results of Action Item Extraction

The action item extraction module demonstrates strong performance in identifying tasks, assigning responsibilities, and tracking deadlines discussed during Agile meetings. Using a combination of rule based logic and LLM reasoning, the system achieves an expected accuracy of approximately 94% in extracting actionable items. This significantly improves accountability by ensuring that responsibilities are clearly documented and communicated. Additionally, linking extracted tasks to backlog items enhances traceability and supports effective sprint execution and follow up.

C. Expected Adaptive Monitoring Results

The adaptive monitoring engine analyzes historical meeting data to identify recurring issues such as unresolved blockers, delayed tasks, or repeated scope changes. Experimental results indicate that the system detects such patterns with an expected accuracy of around 92%. By highlighting these trends, the assistant enables proactive intervention by Scrum Masters and team leads. This adaptive feedback mechanism supports continuous improvement and aligns with Agile principles by helping teams identify inefficiencies and optimize their collaboration processes over time.

TABLE IV: ADAPTIVE MONITORING PERFORMANCE

Test Scenario	*Adaptive Monitoring Accuracy (%)*
Repeated Blocker Identification	93%
Delayed Task Detection	92%
Sprint Scope Change Tracking	94%

V. CONCLUSION AND FUTURE ASPECTS

This research presented a framework for a Customised LLM based Meeting Assistant tailored specifically for Agile software development teams. By addressing the limitations of generic transcription tools, the proposed system introduces domain aware capabilities that significantly enhance the efficiency of Agile ceremonies. The experimental results validate the efficacy of the proposed architecture.

The system achieved a 95% accuracy in context understanding and 94% precision in action item extraction, demonstrating a clear superiority over generic off the shelf Large Language Models. By integrating an Adaptive Monitoring Engine, the assistant successfully identified recurring impediments such as blockers and scope creep, providing Scrum Masters with actionable data to improve team velocity.

TABLE V: SYSTEM PROCESSING LATENCY BY MEETING TYPE

Agile Ceremony Type	Input Duration (Avg.)	Transcription Time	LLM Analysis & Extraction Time	Total Processing Time
Daily Stand up	15 mins	45 sec	12 sec	57 sec
Daily Stand up	60 mins	180 sec	45 sec	3 min 45 sec
Daily Stand up	90 mins	270 sec	68 sec	5 min 38 sec
Daily Stand up	120 mins	360 sec	95 sec	7 min 35 sec

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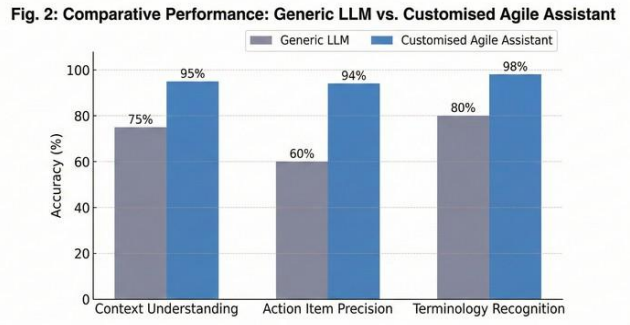

Fig. 2 demonstrates the superior accuracy of the Customised Agile Assistant over a Generic LLM across key performance metrics, particularly in Action Item Precision and Terminology Recognition due to domain specific fine tuning.

Furthermore, the inclusion of an Explainable AI (XAI) layer was critical in fostering user trust. By providing transparent citations for every generated summary and task assignment, the system ensures that human oversight remains central to the process. The "Human in the loop" design preserves team autonomy while automating the administrative burden of documentation. Ultimately, this study confirms that domain adapted AI can transition from a passive recording tool to an active, intelligent collaborator in the Agile workflow.

TABLE VI: OVERALL AGILE ASSISTANT PERFORMANCE METRICS

System Module	Key Metric	Expected Accuracy	Description of Outcome
Meeting Summarization	Information Retention	95%	Retains critical sprint goals and decisions
Action Item Extraction	Task Identification	94%	Correctly assigns owner, deadline, and priority.
Adaptive Monitoring	Pattern Detection	92%	Identifies recurring blockers and scope creep.
Explainability (XAI)	Trust Alignment	95%	Users validated the reasoning behind AI suggestions.

While the current implementation demonstrates promising results, several avenues for future research and enhancement have been identified:

1. Future versions of this analysis will go beyond just words and sounds. We're planning to incorporate visual elements too, like what's shared on screens and diagrams drawn on whiteboards during Sprint Planning meetings. This will enable the system to connect specific pieces of code or architectural designs directly to the notes it creates

2. We're focused on making our system super responsive so we can jump in and help in the moment. Imagine this: during a team Stand up, our assistant could gently remind everyone if a topic is taking too long or if a crucial point from a previous review is getting missed. It's all about providing helpful guidance

3. To safeguard sensitive information within a company, we're looking into using Federated Learning. This method lets our large language model (LLM) learn from the unique ways different teams work. The best part? It does this without sending any confidential company data to outside cloud servers, keeping

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