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**AI in Project Teams: How Trust Calibration Reconfigures
Team's Collaboration and Performance**

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AI in Project Teams: How Trust Calibration Reconfigures Team’s Collaboration and Performance

Abstract

Purpose: As artificial intelligence (AI) becomes increasingly embedded in project-based work, trust calibration, ensuring that trust in AI systems is neither excessive nor insufficient, emerges as a key factor for effective collaboration. This study explores how project professionals calibrate trust in AI and how this process influences team collaboration and performance in technology-mediated project environments.

Design/Methodology: Guided by socio-technical systems theory (STS) complemented by Adaptive Structuration Theory (AST), the study draws on 40 semi-structured interviews with project professionals across diverse UK industries. Thematic analysis is used to explore participants’ lived experiences of trust calibration, collaboration mechanisms, and perceived team performance in AI-supported settings.

Findings: The result indicates that trust in AI is situational, socially distributed, and shaped through ongoing boundary work between human and machine inputs. Enablers such as transparency, role clarity, user experience, cultural norms, and system feedback shape calibration processes. These processes, in turn, influenced collaboration (e.g., delegation of oversight, erosion of informal communication) and performance (e.g., metric-driven evaluation, strategic augmentation of human expertise).

Originality: This study contributes to project management and AI adoption research by conceptualising trust calibration as a socio-technical process embedded in team routines, rather than as an individual attitude. It offers an initial conceptual model and a revised conceptual model that links enablers, practices, and outcomes of trust calibration, demonstrating how trust mediates the relationship between AI integration, collaboration, and performance. Beyond

applying existing frameworks, this research extends STS and AST by developing new theoretical insights into trust calibration as a mechanism linking AI design, collaboration dynamics, and project performance. findings provide practical guidance for designing trust-aware, human-centred AI practices in project environments.

Keywords:

AI Trust in Projects

AI Trust Calibration

Human-AI Collaboration

Project Team Performance

Socio-Technical Systems

Adaptive Structuration Theory

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1. Introduction

Artificial Intelligence (AI), commonly defined as the ability of machines to perform tasks that typically require human intelligence, such as learning, reasoning, and decision-making (Glikson & Woolley, 2020; Kiani, 2025), is increasingly moving beyond its role as a mere efficiency enabler to reshape how work is coordinated, decisions are made, and collaboration unfolds in contemporary organisations (Dwivedi et al., 2023). AI systems are now moving beyond back-end functions to become decision partners, workflow mediators, and creative collaborators in team processes.

These transformations are also visible in project-based work. Project management (PM) refers to the structured use of knowledge, tools, and techniques to execute temporary endeavours and meet defined goals within constraints such as time, cost, and scope (PMI, 2021). In PM contexts, AI is increasingly supporting resource allocation, stakeholder engagement, task automation, and real-time analysis, reshaping how projects are coordinated and delivered (Müller et al., 2024).

Recent national trends illustrate the speed of this transformation: nearly half of large UK organizations report the integration of AI tools into core operations, with widespread application in team communication, collaboration, and task management (Forbes Advisor, 2025). Business leaders are also actively trialling generative AI, with a 2025 PwC survey indicating that over 90% of UK executives are experimenting with such tools, many noting improvements in team performance and decision-making. Within project-based work, a 2025 Association for Project Management (APM) survey shows that more than 70% of professionals perceive AI tools as beneficial for project outcomes, particularly in tracking progress, automating reports, and supporting distributed teams (APM, 2025).

While the PM field has long associated success with traditional performance indicators such as time, cost, and quality, often referred to as the “iron triangle” (Atkinson, 1999), recent studies

increasingly highlight the role of social and behavioural dimensions, particularly trust and collaboration, in shaping project outcomes. For example, Abson et al. (2024) find that trust significantly enables shared leadership, improving project effectiveness. Similarly, Zhou, et al. (2025) show that team readiness, trust in digital tools, and shared leadership are critical human factors that mediate project success. These 'human' success factors become particularly significant as emerging technologies reshape collaborative practices and performance dynamics in project environments.

At the heart of this transformation lies the challenge of trust. As AI systems take on more agency, human-AI collaboration depends not only on technical accuracy, but also on appropriate levels of trust, a challenge increasingly captured by the concept of trust calibration (Okamura & Yamada, 2020). Trust in this context refers to a user's willingness to rely on an AI system, based on its perceived competence, predictability, and alignment with goals (Glikson & Woolley, 2020). Misaligned trust, whether excessive (over-reliance) or insufficient (under-utilisation), does not just affect perceptions of AI; it has tangible effects on collaborative dynamics (e.g., communication, coordination, and role clarity) and performance outcomes (e.g., decision quality, accountability, and efficiency). In this sense, trust calibration operates as a mechanism that shapes both the relational and functional aspects of teamwork in AI-mediated project environments. In this sense, trust calibration functions as a socio-technical mechanism shaping both the relational and functional aspects of teamwork in AI-mediated project environments.

These challenges are salient as AI agents transition from back-end tools to active participants in project teams, providing real-time inputs, recommendations, and autonomous actions. This shift raises new questions about how professionals engage with AI as collaborative partners rather than passive tools (Holzmann & Lechiera, 2022). The issue is amplified in distributed

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and virtual project contexts, where collaboration already depends heavily on digital systems and where AI increasingly functions as both mediator and co-pilot in team processes.

Recent studies in PM have also started to examine how trust and digital technologies shape performance in complex and dynamic project environments, offering important foundations for this research. For example, Princes and Said (2022) show how trust in leadership, performance readiness and situational leadership mediate the relationship between financial sustainability, highlighting trust as a coordination mechanism under uncertainty. Mariani and Mancini (2025) demonstrate that AI capabilities affect project value through organizational agility, highlighting the importance of socio-organizational mechanisms in realizing technological benefits. Building on these emerging debates, this study focuses on trust calibration in AI-enabled project settings, positioning it as a bridging mechanism between technical enablers, collaborative practices, and performance outcomes.

Despite this growing recognition of the importance of trust in PM, existing literature has primarily focused on either the technical features of AI or on user perceptions in isolation, often overlooking the relational and performance-related dynamics that unfold when AI operates as a de facto team member (Müller et al., 2024). To address this gap, this study draws on Socio-Technical Systems (STS) Theory (Trist & Bamforth, 1951), complemented by Adaptive Structuration Theory (AST) (DeSanctis & Poole, 1994), to investigate how trust calibration in AI-enabled systems influences collaboration and performance in project teams. STS provides the foundation for examining how collaboration emerges from the joint optimisation of social and technical subsystems, while AST highlights how technology features are appropriated and enacted in practice.

This qualitative study investigates how project professionals perceive, evaluate, and calibrate their trust in AI-enabled systems during collaborative project work in the UK, where AI

adoption has accelerated across industries, particularly in knowledge-intensive and innovation-driven sectors (Forbes Advisor, 2025). These developments show the need to understand how professionals engage with AI in practice, specifically how trust in these tools is formed, maintained, and adjusted across dynamic, technology-mediated work settings. Accordingly, we pose the following research question:

How does trust calibration in AI systems influence team collaboration and performance in technology-mediated, project-based work environments?

In answering this question, this paper makes several contributions. First, it extends PM literature by integrating the concept of trust calibration into a socio-technical perspective, complemented by AST, offering deeper insights into how collaboration and performance emerge in AI-enhanced teams. Second, it addresses an empirical gap by drawing on the lived experiences of project professionals, moving beyond simulation-based or purely technical studies to capture how trust in AI is negotiated in real project environments. Third, it contributes practical insights for system designers, project managers, and organisational leaders by identifying socio-technical conditions under which AI tools can be trusted and integrated most effectively to support collaboration and performance. Finally, it highlights the relationship between trust, collaboration, and performance, positioning trust calibration as a pivotal mechanism for managing innovation in AI-enhanced project environments.

The remainder of this paper is structured as follows: Section 2 develops the theoretical foundation by positioning trust calibration within STS and AST, and by reviewing literature on AI adoption in PM and trust in technology. Section 3 outlines the research methodology, explaining how qualitative interviews with project professionals were used to explore trust calibration in practice. Section 4 presents the findings, structured around the enablers, practices, and impacts of trust calibration on collaboration and performance. Section 5

discusses the theoretical contributions and practical implications of these findings, while Section 6 reflects on limitations and identifies directions for future research.

2. Theoretical Underpinning and Literature Review

PM studies have historically focused on performance along the lines of the “iron triangle” of cost, time, and scope (Atkinson, 1999). Over the last decade, however, research has increasingly adopted broader, more dynamic conceptualizations of success, including value creation, stakeholder satisfaction, sustainability, and innovation outcomes (Aga et al., 2021; Müller et al., 2019). This shift is closely associated with the rise of agile approaches, which prioritize flexibility, collaboration, and continuous learning. Recent meta-analyses indicate that agile practices positively influence affective, behavioural, and cognitive team outcomes, extending PM performance measures beyond traditional boundaries (Moe et al., 2023).

At the same time, digitalization and the adoption of AI tools are transforming project leadership, governance, and coordination practices (Silvius et al., 2023; Söderlund, 2021). These developments highlight the importance of relational and adaptive capabilities in project teams, providing a fertile context for examining human-AI collaboration. Within this context, theoretical lenses such as Socio-Technical Systems (STS) Theory (Trist & Bamforth, 1951) and Adaptive Structuration Theory (AST) (DeSanctis & Poole, 1994) offer a robust foundation for understanding how project actors appropriate, adapt to, and form trust in AI systems as part of their daily working processes. By integrating these perspectives, research can account for both the structural design of socio-technical systems and the emergent practices through which teams engage with technology.

2.1 Socio-Technical Systems Theory

Originally developed to describe the relationship between social and technical elements in organizational environments (Trist & Bamforth, 1951), STS theory posits that optimal

performance occurs when both social systems (people, roles, norms) and technical systems (tools, processes, technologies) are jointly optimized (Appelbaum, 1997). This perspective is relevant as AI evolves from a passive support tool to an active collaborator in decision-making, collaboration and communication.

Unlike technology acceptance models (e.g., TAM) (Davis, 1989) or individualistic trust frameworks, STS provides a systemic view by recognising that trust, collaboration and performance emerge from interdependent and changing interactions across multiple levels (Trist & Bamforth, 1951). Trust in AI is therefore not merely an individual attitude but an outcome of team-level interaction, system design, and feedback processes (Chowdhury et al., 2022). Accordingly, trust calibration can be conceptualized as a socio-technical process, shaped by AI system design, user expectations, team routines, and communication norms.

STS thus provides an appropriate lens for studying the integration of AI into project teams, where collaboration and trust are co-produced by humans and machines. Building on this foundation, Adaptive Structuration Theory (AST) complements STS by emphasizing how technology features are appropriated and enacted in practice (DeSanctis & Poole, 1994). Together, these frameworks allow trust calibration to be understood as a situated, evolving process arising from socio-technical interactions within teams and organizational contexts.

2.2 Trust in AI

Trust in AI has been a topic of growing interest in various domains and is defined as the tendency to rely on an AI system based on beliefs in its competency, integrity, and predictability (Glikson & Woolley, 2020). However, trust in AI must be adaptable. Researchers increasingly suggest the need for trust calibration, that is, the process by which users align trust levels with what AI systems can and cannot do (Jacovi et al., 2021).

In project teams, with heavy reliance on AI for risk prediction, stakeholder or decision support, over-trust (blind reliance) can result in automation bias and failure to detect system errors, especially in high-stakes environments (Parasuraman & Riley, 1997; Shekar et al., 2024). Under-trust, conversely, can cause duplicated effort, delayed decisions, and resistance to the use of AI outputs (de Visser et al., 2016).

Recent work by Schmidt et al. (2020) and Shin (2021) shows that trust calibration is affected by a number of socio-cognitive factors: mental models of AI held by users, feedback loops, interpretability of system outputs, and transparency of decisions. These factors are important in collaborative project contexts, where collaboration depends on mutual understanding and predictability of team members' (and AI) behavior to ensure that trust is both well-calibrated and contextually responsive for better team coherence and task effectiveness.

2.3 Trust Calibration and Project Team Performance

Experimental studies of AI-mediated collaboration demonstrate the performance consequences of trust calibration. In distributed teams, Binder (2016) found that trust, including trust in technological actors, acted as a substitute for co-presence and proximity influencing collaboration and conflict resolution. Later, Dellermann et al. (2019) documented that moderately calibrated teams, not too trusting and not too distrustful, showing better task distribution, collaboration, and information exchange. Similarly, Seeber et al. (2020) found that teams who overly relied on AI ideas in ideation performed poorly on innovation scores due to offloading cognition and reduced critical thinking, whereas teams that engaged with AI suggestions critically scored higher on creativity and achieved improved outcomes.

The study of Princes & Said (2022), indicate that trust calibration is not only a behaviourally operationalized construct but also a performance-critical skill particularly in agile, high-risk project settings as also discussed by McHugh et al. (2012). Most existing research, however,

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3 treats trust in AI as a static measure or fails to distinguish between over-trust and under-trust
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5 (David et al., 2024) limiting understanding of how project teams dynamically adjust their
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7 application of AI over time, across different phases of project delivery or through learning
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9 cycles.
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12 Several enablers influence the formation and calibration of trust in AI systems within project
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14 environments. Key factors include:
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17 • **Transparency and Explanation:** AI systems that provide explanations aligned with
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19 user expectations improve trust calibration by reducing the “black box” effect and
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21 increasing predictability (Wang et al., 2019).
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25 • **Role Clarity:** Clearly defined responsibilities between human and AI enhance trust
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27 calibration, whereas unclear role boundaries can lead to mis-calibrated trust (Vereschak
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29 et al., 2024).
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33 • **User Experience:** Repeated real-world interaction with AI systems allows users to
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35 align trust levels based on actual performance and reliability (Hoff & Bashir, 2015).
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39 • **Cultural Norms:** Cultural orientation shapes initial trust levels. Individuals from
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41 collectivist cultures exhibit higher baseline trust in AI suggestions, while those from
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43 individualist cultures prefer empirical justification, highlighting the need for culturally
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45 sensitive calibration strategies in globally distributed teams (Kim, 2008).
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48 • **System Feedback:** Learning-based feedback mechanisms in collaborative systems
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50 enable teams to refine mental models of AI capabilities over time (Shneiderman, 2020).
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52 These enablers, summarized in Figure 1, reinforce the socio-technical nature of trust
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54 calibration, suggesting that both technological design choices and organizational strategies are
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56 essential to support effective human-AI collaboration in project settings.
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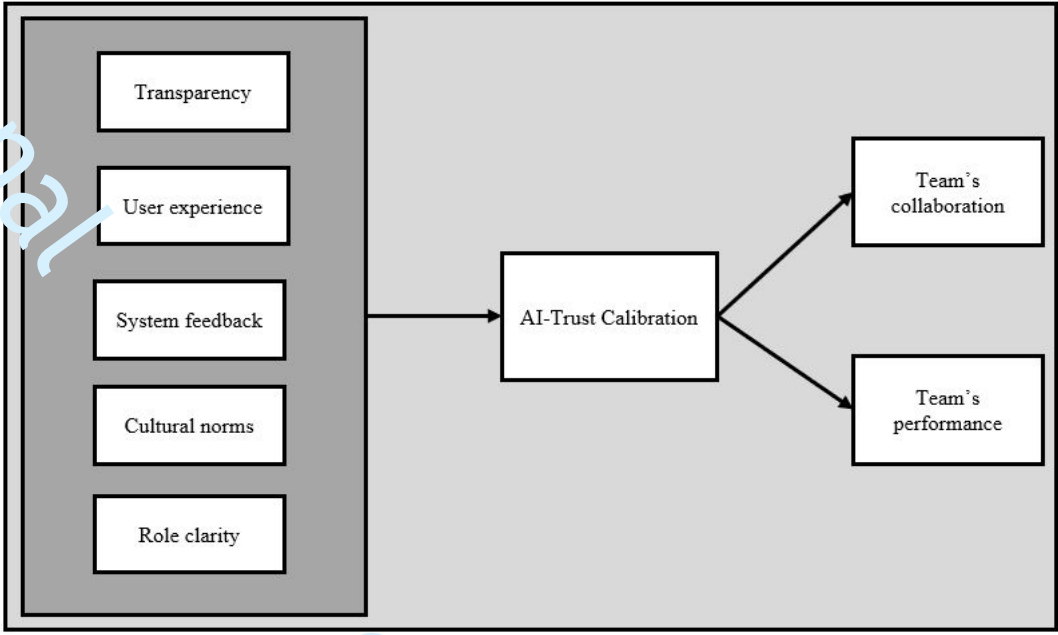


Figure 1: Conceptual model

2.4 AI-Driven Collaboration in Project Teams

The integration of AI into project teams is changing the dynamics of teamwork through the inclusion of non-human members in traditionally human-dominated team structures. AI-based applications now perform tasks ranging from administrative support and real-time decision-making to predictive analytics and autonomous task execution (Dellermann et al., 2019). As they are being incorporated into teamwork workflows, these tools require project teams to adjust their communication habits, mental models, and collaboration mechanisms to accommodate hybrid intelligence systems (Seeber et al., 2020).

Collaboration in these AI-augmented teams is increasingly mediated through digital tools that influence not just how team members communicate, but with whom. AI may serve as an intermediary in task assignment, risk communication, and performance monitoring, thereby reshaping functions and power dynamics in teams (Faraj et al., 2018). However, the success of such hybrid collaborations often hinges on members' trust calibration developing an appropriate level of trust in the AI system's abilities, limitations, and decision rationale

(Glikson & Woolley, 2020). Miscalibrated trust in the form of over-reliance or under-reliance can undermine team performance, hinder decision-making, and ruin interpersonal trust among human collaborators (Komiak & Benbasat, 2006; Okamura & Yamada, 2020).

Existing studies highlight that effective AI-human collaboration is best achieved when AI systems are perceived to be transparent, reliable, and complementary to human decision-making (Wang et al., 2023; Cheong, 2024; Hemmer et al., 2025). According to a 2024 McKinsey Global Survey, 68% of the organizations that used AI tools in project collaboration reported improved decision speed, and 54% reported measurable gains in cross-functional collaboration. In addition, teams that had undergone formal training on AI capabilities and limits were 42% more likely to report successful integration of AI tools into collaborative processes (McKinsey & Company, 2024).

Despite these gains, challenges remain as Zadeh et al. (2024) and Dugbartey & Kehinde (2025) concluded that in agile project teams, AI tools would reinforce current communication silos when poorly aligned with team workflows and norms. The study further discovered that 33% of project teams reported confusion about task ownership when AI agents and humans were assigned overlapping tasks.

3. Methodology

3.1 Research Approach

We adopted a qualitative, interpretivist research approach under a social constructivist epistemology (Cresswell, 2013) to examine how trust in AI is calibrated within project teams and how this process influences collaboration and performance. Such an approach is suitable to better understand complex, situated phenomena like human-AI interaction, where boundaries between technology, behaviour, and context are rather blurred (Creswell, 2015; Yin, 2014).

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The study followed a structured methodology consisting of three phases, as summarised in Table 1 below. Each phase is detailed in the subsections that follow.

Table I: Overview of Research Phases

[Table I Here]

Our study draws on interviews with project professionals based across the UK, spanning sectors such as technology, consulting, and financial services, as well as construction and public sector projects. These sectors were chosen because they are marked by rapid digitalisation, high project intensity, and relatively early adoption of AI-enabled tools (Oyekunle et al., 2024). Including multiple industries ensured variation in project contexts while maintaining focus on environments at the forefront of AI-supported project delivery.

Our participants held roles like project managers, product owners, delivery leads, and technical consultants. This allowed us to explore trust calibration across varied organisational settings while maintaining focus on the shared experience of working in AI-supported project environments.

3.2 Data Collection

A total of 40 semi-structured interviews were collected, with participants recruited through purposive and snowball sampling (Creswell & Guetterman, 2019). Eligibility criteria included: (i) current or recent involvement in AI-enabled project teams, (ii) a minimum of two years’ experience in project environments, and (iii) direct exposure to AI-enabled tools. Participants were selected to ensure variation in seniority, technical expertise, and organisational context. All had at least 2-3 years of experience, with an average of 3-4 AI-enabled projects completed per person. Several had led more than five implementations across business functions.

The participants' AI knowledge levels ranged from general awareness to hands-on applications, and they interacted with systems such as Microsoft Copilot, ClickUp AI, Fireflies, or bespoke enterprise solutions. As shown in Table II, the sample reflects diversity across gender, age, role, sector, geography, experience, and AI tools. This variation enhances the transferability of findings across different project contexts.

Table II: Demographic Details (N=40)

[Table II Here]

Interviews were conducted virtually, lasting between 45 minutes and 90 minutes. Each interview followed an open-ended protocol designed to elicit reflective, experience-based accounts of working with AI in project settings. The core themes generated included 'Enablers of trust calibration', 'Trust calibration practices', and 'Impacts on collaboration and Performance'. All interviews were audio recorded, transcribed verbatim, and supplemented by field notes.

A semi-structured interview guide (Appendix A) was used to ensure thematic consistency across conversations while allowing flexibility for emergent insights.

This stage of the research constituted Phase 2 of our structured methodology, with the explicit aim of capturing diverse, experience-based accounts of trust calibration in AI-supported project teams.

Interviews continued until thematic saturation was achieved, that is, at the point at which no new themes emerged from ongoing analysis (Braun & Clarke, 2021). Saturation was reached after 32 interviews, with subsequent conversations confirming consistency and adding depth to existing themes.

3.3 Data Analysis

This stage of the research constituted Phase 3 of our structured methodology, with the explicit aim of developing conceptually rich insights into trust calibration, collaboration, and performance. Data were analysed using the Gioia methodology (Gioia et al., 2013; Gioia, 2021), which supports inductive theorising from qualitative data. The analysis progressed through three stages: identifying first-order codes, second-order themes, and aggregate dimensions. The data structure illustrating the analytical flow from raw data to theoretical abstraction is presented in Figure 2.

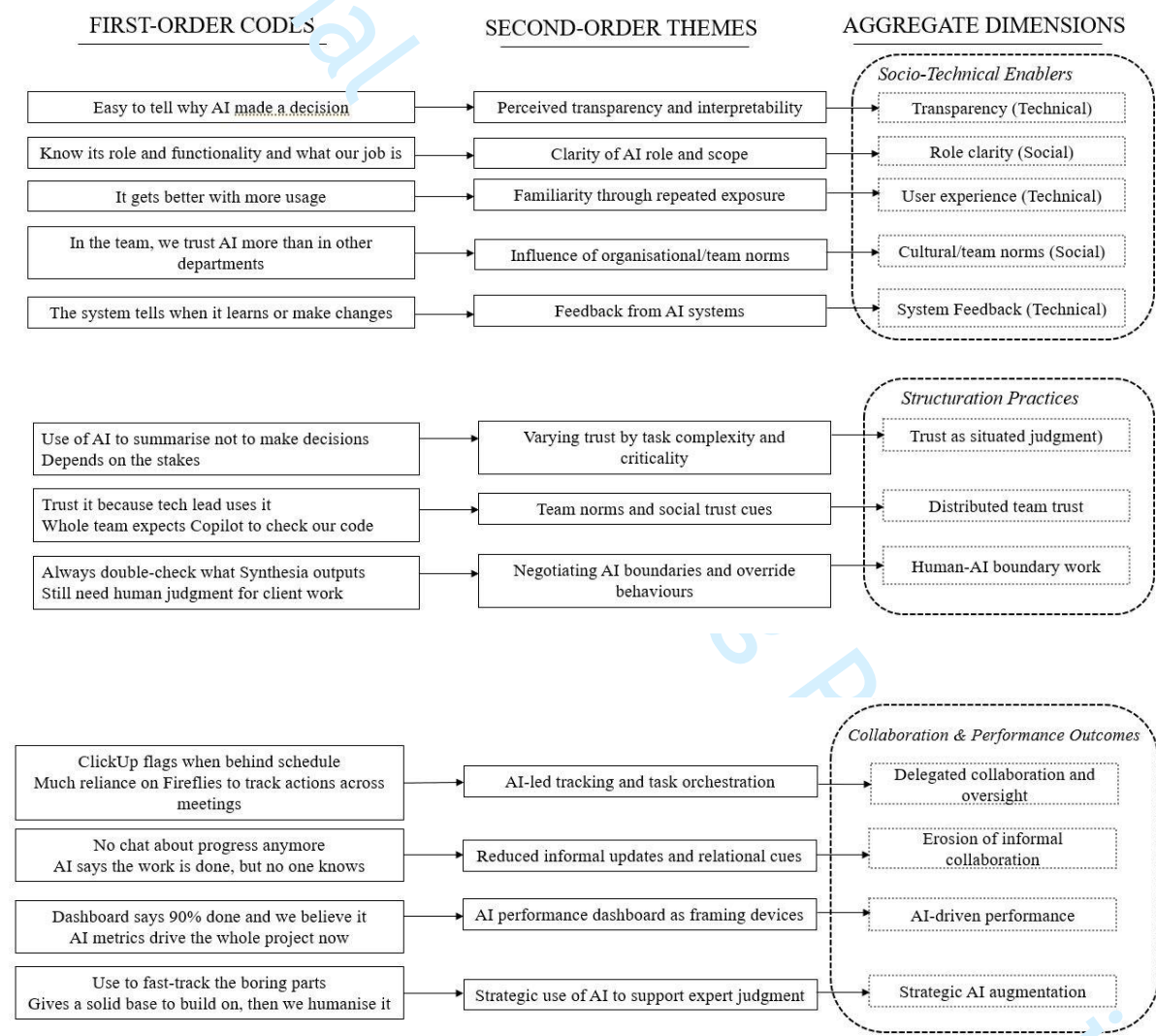


Figure 2: Data Structure

This process was complemented by thematic analysis (Braun & Clarke, 2006; Clarke & Braun, 2016), sensitised by our theoretical framing of STS theory and AST. These perspectives guided attention to how human actors appropriated AI tools, adapted structures, and reconfigured team practices.

To enhance rigour and reduce interpretive bias, a second researcher independently coded a subset of transcripts. Coding discrepancies were discussed and reconciled, resulting in refinement of categories and boundaries. We engaged in iterative memo writing to capture analytical decisions and peer debriefing to critically review emerging themes. These practices enhanced both transparency and reliability.

Illustrative quotes were selected to reflect both widely shared experiences (representative cases) and minority perspectives (contrasting cases), ensuring that findings capture the breadth and diversity of views rather than only dominant narratives.

In line with this analytical framing, the unit of analysis was the project team within its specific organisational project setting. Each ‘project context’ therefore refers to a distinct project environment including its team composition, collaboration routines, and use of AI tools rather than to individual participants in isolation. This framing enabled us to connect personal accounts of trust calibration to team-level collaboration and performance processes within each project.

3.4 Ethical Considerations

Our participants were informed of their right to withdraw at any point, and confidentiality was strictly maintained through pseudonymisation and secure data storage. Ethical reflexivity was maintained throughout the study, with attention to power dynamics in the interview process, transparency in interpretation, and sensitivity to participant anonymity.

4. Findings

Following a systematic coding process and iterative interpretation of the interview data, we identified three aggregate dimensions: ‘socio-technical enablers of trust calibration’, ‘structuration practices of calibration’, and ‘collaboration and performance outcomes’ (cf. figure 2). In line with the STS framework, we view trust calibration not as a discrete or individual judgment, but as a socio-technical negotiation unfolding within teams, shaped by both human and technical subsystems. Complementing this, AST highlights how AI affordances and team routines recursively shape one another through appropriation. These findings empirically validate and extend the conceptual model of trust calibration presented in Figure 1 and reveal that trust in AI is situational, socially distributed, and shaped through boundary work between human and machine inputs.

4.1 Socio-technical Enablers of trust calibration

Enablers captured the conditions within both the technical and social subsystems that made trust calibration possible. Technical enablers included transparency, system feedback, and user experience; social enablers included role clarity and cultural norms as presented in Figure 1. These shaped how trust could be built, distributed, and sustained in project teams.

4.1.1 Transparency (Technical)

Participants repeatedly noted that clear, explainable outputs from AI systems facilitated trust. They reported that trust was easily extended when systems made their reasoning visible or matched human expectations, as in the following comments:

“I trust it more when I understand how it got to the answer...I just ignore the suggestion”
(P13)

“With Fireflies, I can see exactly how it tagged each speaker and what it thinks were the action points...it is not a black box, and that helps” (P13)

“If AI just gives me a number or result without context, I sometimes get suspicious...I want to understand why” (P7)

These reflections show how transparency as a technical affordance enabled smoother collaboration by reducing doubt and avoiding unnecessary re-checks, thereby improving efficiency and confidence in team decisions. Conversely, lack of transparency disrupted collaboration as participants reverted to manual verification, slowing performance.

4.1.2 User Experience (Technical)

Teams built calibrated trust over time, based on consistent system performance. Repeated exposure to a tool's limitations and strengths enabled more accurate expectations, as reported by a few participants:

"After a few months with ClickUp AI, I know what to trust and what to ignore...early on, I was too cautious" (P18)

"It is like working with a new teammate...you need time to know what they are good at" (P27)

"The more I use it, the more I know when to believe it and when to step in" (P14)

Over time, this experiential learning translated into more efficient collaboration and fewer errors, as teams became better at distributing tasks between themselves and AI tools, boosting performance reliability.

4.1.3 System feedback (Technical)

Our findings also revealed that trust calibration improved when AI tools gave feedback on usage or responded to corrections. Teams appreciated systems that learned from interaction, and systems that responded to user input or adapted to team routines were seen as more trustworthy, as in the following verbatim:

"When it starts adapting to our way of working, it feels more like a team member" (P26)

"I trust it more when it adapts...if it keeps making the same mistake, it becomes frustrating" (P3)

Feedback loops reinforced collaboration by allowing AI to integrate into team routines, making interactions smoother and reducing repetitive errors, thereby enhancing performance. Across

enablers, transparency and role clarity were the most consistently cited, emerging as foundational. User experience and cultural norms were situational, while feedback loops, though less common, had powerful effects when present. This suggests a hierarchy of enablers, rather than equal influence.

4.1.4 Role Clarity (Social)

Calibrated trust was also shaped by clarity about the role AI plays in the workflow. Participants felt confident when there was clear separation between AI-suitable tasks and human-led judgment. The following is typical of the participants' sentiments:

"Copilot helps me write code faster, but reviewing it is still on me...this is my rule...AI supports, not decides" (P15)

"We know where it helps and where it does not...clarity is key...you start over-relying and missing stuff" (P30)

"Sometimes we assume the AI will flag something, and it does not ...that's when issues slip through" (P7)

These illustrate how role clarity within the social subsystem preserved accountability and collaboration quality, while blurred role allocation risked over-reliance or neglect, leading to coordination failures and performance issues.

4.1.5 Cultural Norms (Social)

Trust was not just personal; it was often influenced by social cues from team leaders or peers. This reflects distributed trust practices within project teams, as in the following remarks:

"It has become second nature now... mostly because my team lead relies on it and that sends a signal" (P9)

"I was not convinced at first, but everyone else used Copilot, so I gave it a go...kind of peer pressure in a way" (P22)

These examples highlight how leadership modelling and peer adoption shaped collective trust.

This created alignment in collaboration practices, but also risked conformity, where individuals

deferred to group norms rather than independent judgment, with implications for performance resilience.

4.2 Structuration Practices of Trust Calibration

Practices captured the dynamic ways in which teams appropriated AI affordances in context. Guided by AST, these practices illustrate how human judgment and system features recursively shaped one another, producing situated patterns of trust.

4.2.1 Trust as Situated Judgment

Participants consistently reported adapting their reliance on AI tools according to the complexity, ambiguity, and perceived risk of the task at hand. For low-stakes or routine tasks, trust in AI was higher and more automatic; for high-impact, interpretive or strategic tasks, professionals reported increased scrutiny or partial use. The following are typical of the sentiments of the respondents:

“If it is just generating a meeting summary or tracking to-dos, I do not question it...if it is recommending something for a client, I take that with a pinch of salt” (P11)

“I usually use Copilot to draft the skeleton, but I do not trust it to write the whole technical spec...there is no nuance” (P3)

This shows how collaboration practices were task-sensitive: AI was trusted for routine tasks, enabling efficiency, but restricted for strategic work, safeguarding performance quality.

4.2.2 Distributed team trust

Trust in AI was also shown to be socially constructed, shaped by team norms, leadership cues, and shared expectations. When influential team members endorsed or routinised certain tools, others tended to follow suit, even when individual reservations remained, as in the following verbatims:

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“We trust it because our lead engineer uses it...if she is okay with Copilot, then we just go along” (P5)

“A few times I do not think the AI is right...the rest of the team is using it...I do not want to be the odd one out” (P21)

These reflections reveal how trust became embedded in collective routines, streamlining coordination but also risking conformity and suppressing dissent, which could weaken performance resilience.

4.2.3 Human-AI boundary work

Several participants described instances of reasserting human control, in particular, when AI outputs conflicted with domain expertise or client expectations. These acts of override or reinterpretation were not always formalised, but reflected tacit boundary-drawing between human and machine roles, as reported in the following comments:

“We double-check Synthesia’s output before sharing with the client...it is good, but not always context-aware” (P17)

“You still need human sense-making...AI can miss tone or over-simplify” (P9)

Such boundary work preserved critical human judgment in collaboration, ensuring performance outcomes were not undermined by misplaced reliance on AI.

4.3 Collaboration and performance outcomes

Beyond trust calibration, AI tools increasingly mediate team collaboration, providing real-time updates, auto-generated task lists, and performance flags. While these tools improve clarity and reduce friction, they also introduce tensions in informal communication and interpersonal accountability. Our findings demonstrate a causal chain where trust calibration mechanisms shape collaboration processes (delegation, communication patterns, oversight), which in turn

reconfigure team performance outcomes (efficiency, accountability, creativity, and metric-driven evaluation).

4.3.1 Delegated collaboration and oversight

Participants described how AI-driven dashboards, assistants, and trackers had taken on core collaboration tasks such as action item monitoring, deadline reminders, and workload tracking, roles which were traditionally occupied by project leads or team members themselves. The following are typical of participants feelings:

“ClickUp tells me if I am falling behind before my manager does...I feel it has kind of replaced that awkward check-in” (P6)

“Fireflies summarises our meetings and sends out the action points right away...before we even have a chance to argue about what was agreed” (P12)

These show how delegation streamlined oversight but shifted accountability from humans to systems, altering collaboration roles and performance monitoring.

4.3.2 Erosion of informal communication

While AI-supported collaboration was seen as efficient, many noted a decline in informal team touchpoints including impromptu updates, side conversations, or social cues, that previously facilitated team alignment, as in the following verbatim:

“We don’t talk as much about task progress...everyone just checks the board now” (P2)

“Sometimes the tool marks something as complete, but no one knows what actually got done” (P18)

This suggests collaboration became more transactional, weakening relationship-building and shared understanding, which may undermine long-term performance.

4.3.3 AI-driven performance

Our findings also indicated that dashboards and metrics shaped performance perceptions, as reported by some participants:

“If the dashboard says we are 80% done, we tend to believe it...even if there are a bunch of unresolved issues” (P10)
“Sometimes we game the system...just to hit the AI’s targets, not because the work is actually done” (P23)

These reflections show how AI reframed performance in quantifiable terms. While increasing visibility, it risked metric fixation and superficial alignment, potentially obscuring deeper project quality.

4.3.4 Strategic AI augmentation

Despite these challenges, many participants described using AI selectively to enhance, not replace, human expertise., as in the following remarks:

“We use AI to fast-track the boring parts; it gives us something to build on” (P8)
“It is more like a creative partner ...we bounce ideas off it, but we still own the direction” (P20)

This demonstrates how teams achieved hybrid collaboration, using AI to boost creativity and efficiency while retaining human authority, leading to more balanced performance outcomes.

Table III summarises the key enablers, practices, and impacts of trust calibration in project teams. The table maps each theme to illustrative quotes and highlights their implications for collaboration and performance. This structure makes explicit the causal chain observed in our data: trust calibration mechanisms shape collaboration processes, which in turn influence performance outcomes. While all identified themes contributed to this chain, transparency and role clarity emerged as foundational enablers, situated judgments and boundary work reflected

ongoing practices, and delegated oversight and strategic augmentation highlighted the dual opportunities and tensions for collaboration and performance.

Table III. Summary of Findings: Trust Calibration, Collaboration, and Performance

[Table III Here]

5. Discussion

Guided by the STS approach and complemented by AST, our analysis shows that trust calibration operates as a mechanism linking AI design features and team norms to collaboration processes and performance outcomes. This extends existing work by repositioning trust calibration not as a static, individual judgment but as an evolving socio-technical process negotiated at the intersection of technology and human agency.

Our results speak to and extend two current lines of evidence. First, where prior survey research links trust in leaders and situational factors to financial sustainability under complexity (Princes & Said, 2022), we show how trust calibration at the human-AI interface shapes collaboration routines and downstream performance in technology-mediated teams. Second, where AI capabilities have been shown to enhance project value primarily via organizational agility (Mariani & Mancini, 2025), we identify trust calibration as the mechanism that connects technical enablers to social collaborative practices, enabling teams to appropriate AI effectively and translate capabilities into outcomes.

Our findings also indicate that enablers such as transparency, role clarity, and system feedback operate at the technical subsystem level, while user experience and cultural norms stem from the social subsystem. These enablers reflect STS's assertion that work outcomes emerge from the joint optimisation of social and technical elements (Trist & Bamforth, 1951). By showing how these conditions underpin calibrated trust, our study contributes empirical depth to the literature on explainability (Wang et al., 2019; Jacovi et al., 2021) and role delineation in

automation (Vereschak et al., 2024). Our results also suggest a hierarchy of enablers, with transparency and role clarity as foundational, while cultural norms and feedback loops amplify or moderate trust.

Building on AST, we show that trust calibration is achieved through appropriation practices such as situated judgment, distributed trust, and human-AI boundary work. These practices reflect the adaptive structuration of AI tools, where team members not only adopt but reinterpret system rules to fit project contexts (DeSanctis & Poole, 1994). Prior studies often conceptualise trust in automation at the individual level (Hoff & Bashir, 2015; Shin, 2021). Our findings extend this by embedding trust within collective routines and team-level negotiations, where leaders' cues and peer norms guide how AI outputs are appropriated, contested, or overridden.

Moreover, we show that calibrated trust has downstream effects on collaboration and performance. When trust was well calibrated, collaboration routines such as task delegation and progress monitoring were enhanced, echoing prior work on the role of trust in effective project teams (Bond-Barnard et al., 2014; Buvik & Tvedt, 2017). However, system-mediated collaboration also displaced informal communication which is a core resource for sensemaking in projects (Weick & Roberts, 1993; Begemann, Handke & Lehmann-Willenbrock, 2024). Similarly, while AI dashboards provided visibility, they risked reinforcing metric fixation (Muller, 2018) and shifting performance evaluation toward quantifiable outputs at the expense of qualitative impact. These tensions reveal how AI reconfigures not just collaboration routines, but also the very meaning of performance in project settings. In doing so, the study responds to recent calls for more theoretically informed investigations into AI and project work (Müller et al., 2024).

Drawing on these findings, we propose a revised conceptual model, as illustrated in Figure 3, that extends the framework introduced in the literature review, and captures the causal chain observed in our study: socio-technical enablers → trust calibration practices → collaboration processes → performance outcomes. This model not only bridges gaps in the trust-in-automation literature but also extends project management research by theorising how AI reshapes collaboration and performance through trust calibration.

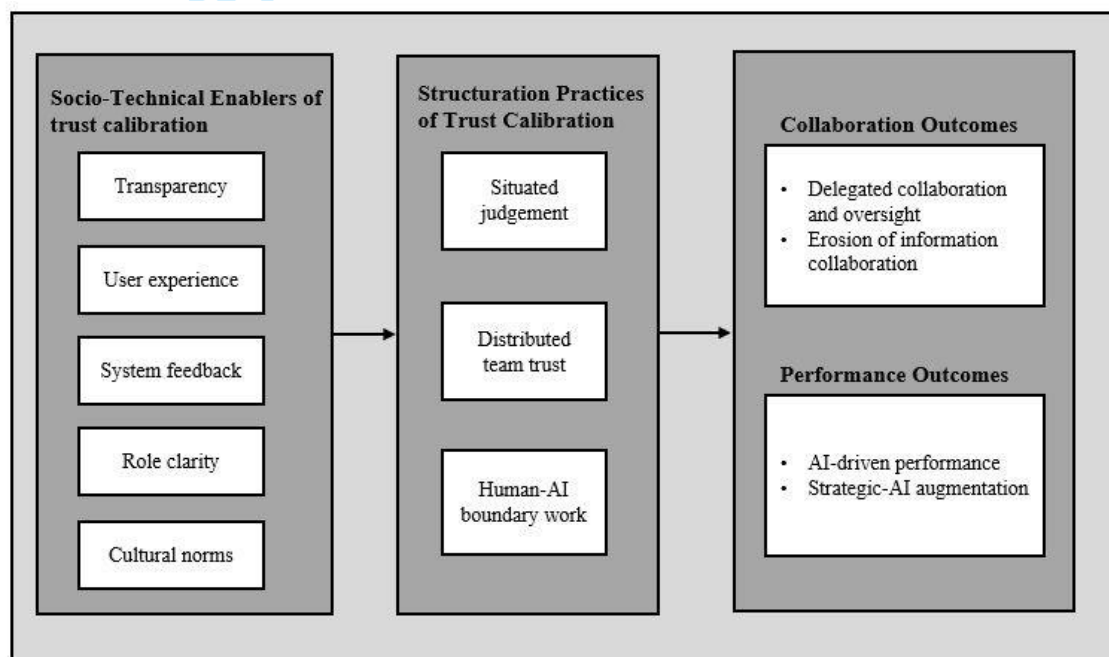


Figure 3: A socio-technical model of trust calibration in AI-enabled project teams
(Authors' work)

5.1 Theoretical Contributions

Our study extends existing theory rather than testing existing models. We extend STS and AST to account for trust calibration as a bridging construct that links AI design features, team collaboration routines, and evolving notions of project performance.

First, this research reconceptualises trust calibration not as an individual cognitive act but as a socio-technical condition involving both technical system affordances (transparency,

feedback) and social team-level dynamics (leadership signals, cultural norms). In doing so, it extends prior work that primarily examined trust in automation at the individual level (Hoff & Bashir, 2015; Shin, 2021) by embedding trust calibration within collective project routines and distributed practices.

Second, by integrating STS with AST, the study advances theory on human-AI interaction. It identifies boundary work and situates appropriation as the key structuration practices through which project professionals negotiate the use of AI tools. Rather than treating adoption as a technical rollout, we frame it as an ongoing renegotiation of authority, accountability, and agency in project contexts. This integration enriches both STS (by emphasising dynamic structuration rather than static balance) and AST (by grounding appropriation in socio-technical interdependence).

Third, the study introduces the concept of AI-mediated performance framing, whereby dashboards, predictive tools, and automated metrics reconfigure how performance is conceptualised and evaluated in project teams. This contribution extends project management literature, which has traditionally centred on the “iron triangle” of cost, time, and quality (Jugdev & Müller, 2005), by showing how algorithmic indicators reshape collaboration norms and prioritisation in digitalised project environments.

These contributions position trust calibration as a bridging construct between AI design features, team collaboration routines, and evolving notions of project performance. Figures 1 and 3 illustrate this contribution: we first propose a conceptual model grounded in the literature (Figure 1) and subsequently refine it through empirical analysis into a revised model (Figure 3) that captures the observed causal chain between trust calibration, collaboration, and performance.

5.2 Practical Implications

Our findings also carry significant implications for project practice, particularly in light of recent adoption trends. Surveys indicate that over 70% of UK-based project professionals now use AI tools for progress tracking and coordination, and more than 90% of executives are piloting generative AI in business operations (APM, 2025; PricewaterhouseCoopers, 2025). However, research also shows that only 20% of low-AI-maturity organisations sustain initiatives beyond three years, compared to 45% among high-maturity firms (Gartner, 2025). These figures underline the urgency of moving beyond functional adoption toward developing the human and organisational capabilities needed for sustained integration.

First, project teams require more than functional knowledge of AI tools; they need support in developing trust calibration skills. Participants frequently described regular interaction with AI tools such as Microsoft Copilot, ClickUp AI, and Fireflies. However, their reflections also suggested that using these systems in daily project routines did not necessarily translate into deeper technical understanding. This gap highlights risks of both over-reliance and under-utilisation, underscoring the need to build trust calibration skills beyond functional use. Building trust calibration capacity through experiential training, feedback analysis, and critical reflection practices is therefore essential to mitigate risks such as automation bias or AI neglect.

Second, project leaders must recognise that their behaviour sets the tone for team trust in AI. Our findings show that trust is often socially distributed, with team members looking to peers or supervisors for cues on whether to rely on AI outputs. This aligns with earlier research on distributed trust (Kramer, 1999) and reveals the need for leaders to model responsible use. When leaders demonstrate balanced engagement with AI, open to its support but critical of its limitations, they create a psychologically safe space for others to question, adapt, or override AI recommendations. Leadership development programmes should thus explicitly incorporate training on AI literacy, trust signalling, and reflexive decision-making.

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Third, organisations must be cautious not to let AI displace the human elements of team collaboration. While tools like ClickUp and Fireflies automate coordination and streamline oversight, several participants noted a reduction in informal team interactions such as check-ins, clarifications, or spontaneous problem-solving that once promoted shared understanding. As collaboration becomes increasingly system-mediated, it is vital to reintroduce human-centric practices, particularly in distributed or hybrid project settings where interpersonal cues are already limited. Reinstating brief team huddles, informal feedback loops, and retrospectives can help preserve the relational fabric of the team and ensure that AI enhances, rather than erodes, cohesion.

Fourth and final, the framing of performance must evolve alongside the use of AI. While over 70% of project professionals now rely on AI dashboards for progress visibility (APM, 2025), our participants reported instances of ‘gaming the system’ to satisfy machine logic rather than real progress. This reinforces the need for multi-dimensional performance frameworks that combine AI indicators with qualitative assessments and stakeholder narratives, mitigating the reductive pull of algorithmic benchmarks.

6. Limitations and Future research

6.1 Limitations

Despite the theoretical and practical contributions into trust calibration in AI-mediated project environments, our study also has limitations that need to be looked upon by researchers when using its findings. First, the sample was geographically restricted to project professionals in the UK, primarily from technology-intensive sectors such as consulting, tech, and financial services. As such, the findings may not be fully transferable to industries with different levels of digital maturity or work practices, such as public sector, education, or healthcare. Future studies should therefore be cautious about generalising beyond the specific context examined in this study. Second, the data were drawn from self-reported interviews, which are inherently

interpretive and may be influenced by selective memory or social desirability bias. Although the use of reflexive interviewing and triangulation enhanced validity, the accounts reflect participants' perspectives rather than direct observation of behaviour. Moreover, the study focused on team-level insights but did not systematically disaggregate by factors such as seniority, function, or specific AI tool type. These variables may shape how trust is developed or distributed within teams but were beyond the scope of this analysis. In addition, while our analysis was guided by STS and complemented by AST, we did not explicitly compare socio-technical dynamics across different organisational levels (individual, team, organisational), which may offer further theoretical insights. Finally, future work could also quantitatively test the revised model, for example through surveys or experiments, to examine how enablers, practices, and outcomes of trust calibration predict collaboration and performance across larger samples.

6.2 Future Research

Our study provides avenues for future work. For instance, scholars can explore how trust calibration evolves over time, in particular as AI systems become more autonomous and teams gain (or lose) familiarity with them. This can be done through longitudinal studies to reveal how trust trajectories stabilise or shift across different project phases. Future research can also consider diversity and inclusion as important variables, that is, how cultural, gender, or cognitive differences influence individuals' willingness to trust AI and how marginalised or minority groups experience AI differently in collaborative environments. In addition, as AI plays a larger role in decision-making, future research could examine how responsibilities are distributed between human and machine agents, particularly in high-stakes or regulated environments. Cross-sector and cross-country comparative studies would also be valuable, to test whether the patterns of trust calibration we observed in UK-based, digitally intensive sectors extend to different cultural and institutional settings. Finally, further work could

explicitly link trust calibration to long-term measures of project collaboration and performance, such as innovation outcomes, client satisfaction, or sustainability of AI integration.

7. Conclusion

This study examined how trust in AI is calibrated within project teams and how this calibration shapes collaboration practices and performance perceptions. Guided by the STS theory and complemented by AST and drawing on qualitative data from UK-based project professionals, we found that trust in AI is neither fixed nor solely individual, but it is a dynamic, socially distributed process influenced by team norms, leadership signals, and task criticality. AI systems are not simply tools but active participants in project collaboration, with the potential to both enhance and complicate workflows. Moreover, trust calibration emerged as a core mechanism through which teams manage the integration of AI into their collaborative routines. Participants engaged in ongoing human-AI boundary work, adjusting their reliance on machine outputs while preserving professional judgment. While AI tools enabled faster oversight and performance visibility, they also risked undermining informal collaboration and reinforcing metric-driven behaviours. Our study contributes to PM literature by providing a more holistic view of AI adoption, not as a technical upgrade, but as a relational and organisational shift. In doing so, it extends STS and AST by positioning trust calibration as the bridge between technological affordances, social norms, and performance outcomes. As AI continues to permeate project environments, the challenge for practitioners and researchers alike is not whether to trust AI, but how to calibrate that trust in ways that support both efficiency and human agency.

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Table I: Overview of Research Phases

Phase	Focus	Activities
Phase 1: Recruitment and Sampling	Identify and select participants	Targeted project professionals across multiple sectors; ensured variation in roles, industries, and geographies
Phase 2: Data Collection	Conduct interviews	Semi-structured interviews to elicit in-depth accounts of AI use, trust calibration, collaboration, and performance
Phase 3: Analysis	Code and interpret data	Iterative coding, theme development, and interpretation to generate theoretical insights

Table II: Demographic Details (N=40)

Attribute	Categories
Gender	Male (24), Female (16)
Age Bracket	25-34 (10), 35-44 (15), 45-54 (9), 55+ (6)
Location	UK (40)
Role	Project Managers (20), Product Owners (6), Delivery Leads (5), Consultants (9)
Industry Sector	Technology (12), Consulting (10), Financial Services (8), Construction (5), Public Sector (5)
Years of Experience	2-25 years
Interview Duration	45-90 minutes
AI Tools Used	MS Copilot, Fireflies, ClickUp AI, Jira, bespoke enterprise systems

Table III. Summary of Findings: Trust Calibration, Collaboration, and Performance

Theme	Illustrative Quote	Implications for Collaboration & Performance	STS/AST Lens
Transparency	“With Fireflies...I can see exactly how it tagged each speaker” (P13)	Builds confidence, reduces ambiguity, enhances coordination efficiency	Technical subsystem (system affordance)
User Experience	“After a few months...I know what to trust and what to ignore” (P18)	Improves calibration over time, reduces errors, boosts reliability	Technical subsystem (experiential learning)
System Feedback	“When it adapts to our way of working, it feels more like a team member” (P26)	Reinforces integration of AI into routines, smoother collaboration	Technical subsystem (feedback loop)
Role Clarity	“Copilot helps me write code faster, but reviewing it is still on me” (P15)	Prevents over-reliance, preserves accountability and quality	Social subsystem (task boundaries)
Cultural Norms	“My team lead relies on it...that sends a signal” (P9)	Trust distributed socially; team norms reinforce or suppress adoption	Social subsystem (leadership/peer cues)
Situated Judgment	“For meeting summaries, I don’t question it...for clients, I’m cautious” (P11)	Task-sensitive calibration; protects critical performance outcomes	Structuration practice (situational appropriation)
Distributed Team Trust	“We trust it because our lead engineer uses it” (P5)	Social construction of trust; aligns team behaviour but risks conformity	Structuration practice (peer/leader influence)
Human-AI Boundary Work	“We double-check Synthesia’s output before sharing” (P17)	Maintains human authority in high stakes tasks, safeguards quality	Structuration practice (boundary negotiation)
Delegated Collaboration and Oversight	“ClickUp tells me if I’m falling behind before my manager does” (P6)	Efficiency gains: shifts oversight from people to systems	Collaboration/performance outcome (delegated monitoring)
Erosion of Informal Communication	“We don’t talk as much about task progress...everyone just checks the board” (P2)	Reduces relational cohesion; collaboration becomes transactional	Collaboration/performance outcome (loss of social glue)

AI-driven Performance	“If the dashboard says we’re 80% done, we tend to believe it” (P10)	Shapes performance framing; risks metric fixation	Collaboration/performance outcome (algorithmic framing)
Strategic AI-Augmentation	“It is more like a creative partner...we bounce ideas off it” (P20)	Hybrid use enhances creativity, preserves human authority	Collaboration/performance outcome (hybrid collaboration)

Reviewer 1**Response:**

We thank the reviewer for their positive feedback. We appreciate the recognition of our efforts to strengthen the paper during the previous revision round.

Reviewer 2**Comment:**

The authors have responded to most of my previous comments. I have only one minor remark: the unit of analysis is not yet clear. What does exactly “project context” mean? Is it the project? The project team? Please clarify this point and choose a non-ambiguous expression.

Response:

We thank the reviewer for this valuable comment. In response, we have clarified the definition of the unit of analysis in Section 3.3 (Data Analysis). The manuscript now explicitly states that the unit of analysis is the project team within its specific organisational project setting. The change is reflected on page 16 (highlighted in yellow). We believe this clarification ensures terminological precision and aligns the analytical level with the study’s focus on team-level collaboration and performance.