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Organizational Barriers to Implementing Artificial Intelligence Technologies in Engineering Team Workflows

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Abstract

Artificial intelligence is increasingly embedded in engineering team workflows; yet, sustained use often weakens after initial uptake, resulting in patterns of superficial compliance, concealed workarounds, or complete discontinuance. This article aims to explain post-adoption trajectories by developing a conceptual model of organizational barriers that shape long-term use of artificial intelligence tools in engineering work, with software development and coding assistants used as an illustrative domain. Based on a structured synthesis of recent scholarship on technology adoption, trust in artificial intelligence, cognitive load, and employee resistance to digital transformation, the study derives an integrative framework that links individual evaluations to organizational conditions. The model specifies five constructs—usefulness, trust, challenges (technical, cognitive, emotional, and process-related), organizational influence, and disengagement triggers—and articulates how their interaction shifts behavior from sustained engagement to minimal or avoided use. As a result, the article (i) proposes a barrier taxonomy relevant to engineering teams, distinguishing infrastructure and integration constraints, cognitive–emotional strain, procedural and regulatory misalignment, cultural and power dynamics, and managerial–strategic inconsistency; (ii) maps these mechanisms onto established adoption logics to show where intention-focused explanations fail to capture withdrawal dynamics; and (iii) formulates research propositions describing how organizational practices moderate the link between perceived value and real usage, and how status, identity, autonomy, and perceived fairness threats catalyze disengagement. To facilitate empirical verification, the paper outlines a planned mixed-methods design that combines large-scale secondary survey evidence on developer tool use with primary qualitative data from engineers and engineering leaders to reconstruct post-adoption pathways and identify disengagement triggers in situ. The article is intended for researchers studying technology adoption and organizational behavior, as well as for engineering managers, transformation leaders, and governance functions seeking to design workflows, policies, and incentives that support the durable, auditable, and trusted use of artificial intelligence.

Keywords: *Artificial Intelligence Adoption, Disengagement Triggers, Engineering Workflows, Organizational Barriers, Trust in Artificial Intelligence.*

INTRODUCTION

Artificial intelligence technologies are rapidly being embedded in the work practices of engineering teams, spanning design and analysis, data management, and decision support. One of the fastest-developing directions involves the use of AI coding assistants in software engineering teams across the SDLC: code generation and refactoring, testing, documentation, and support for code review. Yet as AI deployment scales, a paradox emerges: despite broad availability and widely reported benefits, these tools are often used superficially, inconsistently, or only nominally, while a subset of specialists gradually reduces their usage intensity or abandons them entirely. This disengagement/discontinuance phenomenon points to organizational barriers that cannot be explained solely by model quality or tool functionality.

Classical technology adoption frameworks—Technology Acceptance Model (TAM) and Technology–Organization–Environment (TOE)—suggest that user behavior is shaped not only by technological characteristics, but by perceived usefulness, ease of use, and organizational and environmental conditions. In AI adoption, attention increasingly shifts to the post-adoption stage: why usage fails to stabilize after initial acceptance, and how the interplay of trust in AI, cognitive load, emotional responses, and organizational influence produces trajectories from active use to minimal compliance with expectations or to rejection. The present study examines

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these mechanisms for engineering workflows broadly, with a specific emphasis on software development and AI coding assistants as a representative domain.

The article aims, through a structured synthesis of recent literature, to propose a conceptual model of organizational barriers to the adoption and sustained use of AI technologies in the workflows of engineering teams, with a particular focus on software development teams (SDLC) and on disengagement/discontinuance after the initial acceptance of AI coding assistants.

To meet this aim, the study addresses four objectives:

1. to systematize research on AI technology adoption in engineering teams using TAM and TOE as reference frameworks, and to show the limits of these approaches in explaining sustained use;

2. to integrate findings on trust in AI, cognitive load, emotional responses, and user experience into a unified set of disengagement factors;

3. to formulate a conceptual model comprising five core constructs (usefulness, trust, challenges, organizational influence, disengagement triggers) and to describe their functions in sustaining AI use in engineering workflows;

4. to outline the design of a planned mixed-methods study with a dedicated SDLC case (Stack Overflow Developer Survey plus a new qualitative survey/interview component), enabling construct operationalization and the identification of disengagement triggers.

The study's contribution is threefold: (1) it offers a targeted integration of TAM and TOE tailored to engineering teams, interpreting perceived usefulness and trust in AI through the lens of risk, reliability, and human–AI interaction in safety- and mission-critical tasks; (2) it introduces disengagement triggers as a systematic construct linking organizational practices to engineers' cognitive and emotional reactions and to observed post-adoption behavior; (3) it substantiates a conceptual model of organizational barriers to sustained AI use, suitable as a theoretical basis for future empirical work and for designing managerial interventions that reduce the likelihood of persistent disengagement/discontinuance.

LITERATURE REVIEW

To develop the conceptual model, the study drew on publications from the last five years addressing AI and digital technology adoption, trust in AI, resistance to digital transformation, and the organizational and behavioral effects of AI implementation.

As the theoretical basis for analyzing technology adoption models, the study relies on S. Afroogh et al. [1], who systematically examine drivers of trust and distrust in AI and show that trust in AI functions both as a facilitator of adoption and, when insufficient, as a barrier; and on S. Chatterjee et al. [2], who propose an extended AI adoption model for manufacturing organizations grounded in TOE and a hybrid TOE–TAM configuration, evidencing the salience of technological, organizational, and environmental conditions. In an integrative review of resistance to digital transformation, V. Cieslak and C. Valor [3] explain how perceived threats to resources and work identity generate emotional responses and resistant behaviors, which is informative for conceptualizing disengagement triggers in engineering teams. I. Golgeci et al. [4] analyze organizational resistance to AI and propose a process-oriented framework that differentiates sources of resistance (fear, feelings of incompetence, negative attitudes) and identifies organizational mechanisms for mitigation through AI accessibility, a focus on human–AI augmentation, and the legitimation of the technology. Based on a reflexive thematic analysis of human–AI interactions, M. T. Khan et al. [5] describe how trust in AI is constructed in a "trust, but verify" mode, shaped by transparency, explainability, and cognitive load, and show that excessive cognitive load intensifies vigilance and reduces willingness to engage with AI tools in a deep and sustained manner. Z. Liu et al. [6] demonstrate that organizational awareness of AI can increase knowledge-hiding behavior, which is mediated by psychological availability and moderated by person–organization fit. This supports an interpretation in which the introduction of AI into engineering workflows can activate disengagement through concerns about loss of distinctiveness and status threats. M. Y. B. Masod and S. F. Zakaria [7] examine AI adoption in the manufacturing sector through TOE, emphasizing organizational readiness, leadership, and resourcing, alongside technological constraints such as complexity, compatibility, and data quality. S. Na et al. [8] apply TAM in combination with TOE to study AI adoption in construction firms, highlighting the centrality of perceived usefulness and perceived ease of use, strengthened by managerial support and organizational culture. E. Sánchez et al. [9] investigate AI adoption in small and medium-sized enterprises using a TOE–DOI approach, finding that resource scarcity, uncertainty in strategic objectives, and external pressures substantially shape adoption decisions. Finally, Y. Song et al. [10], using evidence from business organizations, demonstrate that top management influences AI adoption through perceived usefulness and perceived ease of use. That implementation is associated with gains in efficiency and deeper technology adoption, which is informative for interpreting organizational influence in engineering teams.

Accordingly, the reviewed corpus comprises ten scholarly publications covering: (1) technology adoption theory and models (TAM, TOE, and hybrid or derivative models); (2) trust in AI and human–AI interaction; (3) organizational and affective resistance to digital transformation; (4) AI-related effects on employee knowledge and behavior; and (5) industry settings adjacent to engineering team environments (manufacturing, construction, industrial, and project-oriented organizations).

PROPOSED RESEARCH DESIGN

For the empirical assessment of the proposed conceptual model, a planned mixed-methods design is proposed, combining secondary quantitative evidence with primary qualitative data. The choice of a mixed design follows the logic of integrating adoption-related constructs with organizational and behavioral mechanisms that unfold after initial acceptance, as suggested by prior TOE–TAM and hybrid configurations, as well as research on post-adoption dynamics and resistance to AI-enabled change [2; 4; 8–10].

Data source 1 (quantitative). This dataset serves as a large-scale empirical foundation for examining patterns of AI tool use in software development (SDLC) and for assessing the relationships between work-setting characteristics and user attitudes toward AI-enabled work practices [2; 8; 10]. In analytical terms, the survey offers an opportunity to compare usage intensity and adoption-related perceptions across different organizational settings, seniority levels, and task profiles, aligning with the technological, managerial, and environmental domains emphasized in TOE-oriented work on AI adoption [2; 7; 9].

Data source 2 (qualitative). Primary qualitative data will be collected from members of engineering teams, including software developers and engineering leaders. The interview/survey protocol will be structured around the five constructs of the model (perceived usefulness, trust in AI, challenges—technical/cognitive/emotional/process, organizational influence, disengagement triggers) and will focus on identifying drivers of reduced usage, nominal compliance, and discontinuance mechanisms following initial adoption [1; 3]–[6]. Conceptually, this design draws on evidence that trust formation in human–AI interaction is frequently enacted through verification practices and is sensitive to cognitive load, transparency, and explainability pressures [1; 5], while disengagement can be shaped by resource-threat perceptions, identity and status concerns, and organizational practices surrounding technology legitimation and governance [3; 4; 6].

For the quantitative component, the analysis will rely on descriptive statistics and the identification of stable usage patterns, with attention to how these patterns vary across contextual conditions relevant to TOE and TAM constructs [2; 7]–[10]. For the qualitative component, thematic coding will be applied, supplemented by topic modeling to derive a typology of disengagement triggers and organizational barriers grounded in participant narratives and recurring themes [3–6]. Findings will be articulated as tests of the study's research propositions; no claims about proven effectiveness or causal impact will be made until empirical evidence has been collected and analyzed.

PROPOSED CONCEPTUAL FRAMEWORK

A conceptual framework is proposed below in which five core constructs (usefulness, trust, challenges, organizational influence, and disengagement triggers) account for post-adoption trajectories leading to disengagement/discontinuance. Building on analyses of hybrid TAM–TOE models, the framework posits that individual evaluations of perceived usefulness and trust in AI are mediated by organizational conditions and, in turn, shape the depth and persistence of AI use. Chatterjee et al. [2] show that combining TAM and TOE enables simultaneous consideration of technological, organizational, and environmental determinants of AI adoption. A similar logic is advanced by Na et al. [8], who develop an integrative research framework for construction firms in which TAM constructs (perceived usefulness, perceived ease of use, attitude, and behavioral intention) are explicitly linked to technological, organizational, and environmental variables derived from the TOE framework. Their model illustrates this integration: external variables grouped by TOE domains (technological, organizational, and ecological) shape perceived usefulness and perceived ease of use, which then influence attitudes toward use and users' behavioral intentions [8]. This logic transfers well to engineering teams if the technological domain is interpreted as the combined set of AI tool characteristics and their compatibility with established engineering processes, the organizational domain as culture, leadership, resources, and power structures within the unit, and the environmental domain as regulatory pressure, industry standards, and competitive dynamics (see Fig. 1).

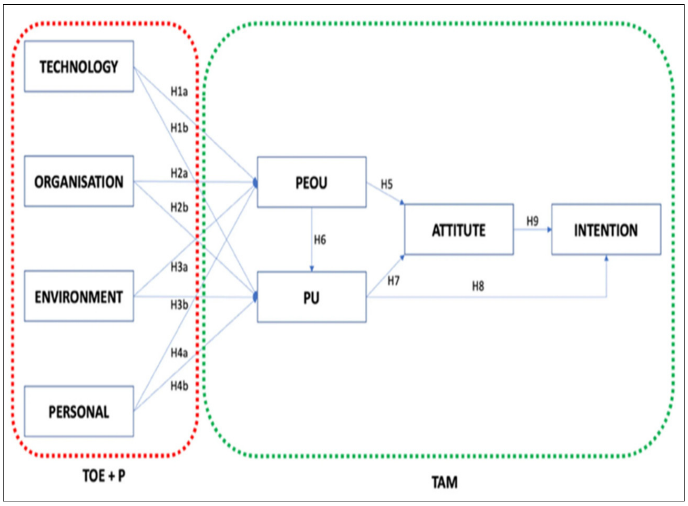

Figure 1. Research model in [8]

Within the proposed conceptual model, organizational barriers are expressed through the ways in which the organization sets interpretive and operational boundaries for engineers' perceptions of AI. When organizational practices amplify uncertainty—through lack of strategy, inconsistent leadership signals, or fragmented pilots without sustained support—even potentially high perceived usefulness may fail to translate into stable use. Engineers can interpret AI as a short-lived trend, a marginal experiment, or a career risk. By contrast, aligned leadership, explicit linkage between AI initiatives and unit objectives, dedicated resources for training, and participatory workflow redesign create conditions in which trust in AI and perceived usefulness are reinforced through experience and mutually strengthen one another [4; 8–10].

A distinctive position in the model is assigned to disengagement triggers—organizational and situational factors that initiate engineers' withdrawal from active interaction with AI. Literature on resistance to digital transformation indicates that persistent resistance is often driven not by isolated technological shortcomings but by a cumulative experience of resource threat: time, status, identity, and control over tasks [3]. In AI implementation, such triggers can include top-down deployment without meaningful team deliberation; reliance on performance metrics perceived as unfair or insensitive to the real complexity of engineering work; and lack of transparency regarding how data from AI tools are used in employee performance evaluation.

Liu et al. [6] show that heightened organizational awareness of AI can, under certain conditions, intensify knowledge-hiding behaviour, especially when person–organization fit is low. In engineering teams, an analogous mechanism can manifest as covert refusal to share know-how, deliberate circumvention of AI tools, or intentionally shallow usage aimed at preserving control over critical knowledge domains. These forms of disengagement are not always visible to managers, yet they materially undermine sustained AI use.

Taken together, the synthesized literature supports a set of research propositions suitable for testing in future empirical studies of engineering teams. First, perceived usefulness is treated as a necessary but insufficient condition for sustained AI use: under low trust in AI, high cognitive load, and weak organizational influence (unclear strategy, insufficient resources), even high perceived usefulness is likely to yield only sporadic and task-specific use [1; 4; 5; 8–10]. Second, the proposed model anticipates that organizational factors moderate the relationship between perceived usefulness and actual AI use in engineering processes [2; 7–9]. Third, disengagement triggers associated with threats to status, identity, and control are expected to mediate the influence of the organizational environment on trust in AI and on resistance or passive acceptance behaviours, including supervisory scepticism, minimal compliance, and knowledge hiding [3; 4; 6].

The review-based results enable a reinterpretation of organizational barriers to AI implementation in engineering teams by linking them to the article's five constructs. First, perceived usefulness and trust in AI cannot be treated independently of organizational influence: leadership practices, allocation of authority, training, and incentive structures shape how these constructs translate into engineers' concrete decisions to use AI. Second, the spectrum of difficulties extends beyond conventional "technical problems" and encompasses cognitive, affective, and process-related components. Third, research on resistance to digital transformation and organizational resistance to AI suggests that persistent disengagement is often the result of the accumulation of triggers rather than a single adverse incident [3; 4].

Applying these ideas to engineering teams enables the identification of several clusters of organisational barriers as primary candidates for disengagement triggers. Their synthesis is presented in Table 1.

Table 1. Prominent clusters of organizational barriers to AI implementation in engineering teams [4]

Barrier Group	Typical Manifestations in Engineering Teams	Related Article Constructs
Technical and Infrastructure	Complex integration of AI into existing CAD/CAE/PLM and DevOps pipelines; data quality issues; security and access constraints	perceived usefulness; technical challenges
Cognitive and Emotional	Overload from interfaces and notifications; anxiety about the quality of AI outputs; fear of devaluation of engineers' expertise	trust in AI; cognitive load; emotional barriers
Process and Regulatory	No revision of procedures and policies; unclear accountability for AI-related errors; conflicts with industry standards and certification requirements	organizational influence; process barriers
Cultural and Power-Related	Dominance of informal expert hierarchies; stigmatization of AI use as "cheating"; conflicts between "digital" and "traditional" engineers	organizational culture; disengagement triggers
Managerial and Strategic	Inconsistent leadership signals; pilots without sustained support; lack of resources for training and AI configuration	organizational influence; perceived usefulness; trust in AI

Process and regulatory barriers are particularly significant in engineering settings, where a substantial portion of work is grounded in standards, regulatory requirements, and quality assurance procedures. When AI is not embedded into these formal controls, it becomes a "shadow" tool whose use is difficult to justify to external auditors and internal compliance functions. Under such conditions, even strong trust held by individual engineers does not translate into organization-wide acceptance of the technology. Cultural and power-related barriers manifest, for example, in the stigmatization of AI use as a sign of "unprofessionalism" or "laziness," which encourages concealed use of AI and superficial adoption of its outputs. Managerial and strategic barriers form the background for all other groups: inconsistent leadership signals, the absence of a long-term AI roadmap, and resource scarcity intensify emotional and cognitive strain and contribute to the accumulation of disengagement triggers [3; 4; 7; 9].

The next step in the discussion concerns how the proposed conceptual model relates to the classical TAM and TOE frameworks and what theoretical value is added by emphasizing disengagement triggers. For this purpose, it is appropriate to align the five core constructs of the article with the TAM and TOE components, as well as the anticipated effects on engineering workflows (Table 2).

Table 2. Mapping of the model's core constructs to TAM and TOE in engineering workflows, with an illustrative SDLC example [2, 8, 10]

Construct	Related TAM/TOE Components	Expected Influence on Engineering Workflows	Potential Disengagement Triggers
perceived usefulness	TAM: perceived usefulness; TOE: technological domain (benefit, compatibility)	Degree to which AI is integrated into critical tasks (incl. SDLC: code writing and refactoring, code review, testing, debugging, documentation, CI/CD support)	Mismatch between realized value and expectations; unintended side effects and risk exposure
trust in AI	TAM: modifier of attitude toward use; TOE: technological and organizational domains	Readiness to rely on AI recommendations, reducing duplicated effort and repeated verification loops	Trust-breaking incidents, opaque decisions, unclear failures and error patterns
Challenges and barriers (technical/ cognitive/ emotional/process)	TAM: perceived ease of use; TOE: technological and organizational domains	Maintenance or growth of process complexity; emergence of additional "workarounds" around AI	Burdensome interfaces, lack of support, conflicts with established procedures
Organizational influence	TOE: organizational domain (structure, resources, culture, leadership)	Institutionalization of AI via standards, practices, training, and incentive systems	Contradictory signals, lack of resources, weak leadership sponsorship
disengagement triggers	Not explicitly represented in TAM/TOE; derived from the interaction of conditions and perceptions.	Transition to shallow, symbolic, or concealed AI use; eventual abandonment of tools	Threats to status, identity, autonomy, and perceptions of fair evaluation

Table 2 shows that TAM and TOE effectively describe AI adoption at the level of intentions and broad organizational–environmental conditions, while the mechanisms driving disengagement remain insufficiently specified. The construct of disengagement triggers, derived from research on resistance to digital transformation and on employee behavior under technology-driven change [3; 4; 6], extends these frameworks by making explicit the pathway from the combination of low trust in AI, elevated cognitive load, and unfavorable organizational influence to persistent withdrawal from AI use.

The paper outlines a planned empirical study design capable of testing the proposed model in engineering workflows. A mixed-methods approach appears well suited, combining: (1) analysis of Stack Overflow Developer Survey data as an SDLC-focused case to identify AI use patterns and contextual differences; (2) a new qualitative survey and/or semi-structured interviews with members of engineering teams (including software developers and engineering leaders) to reconstruct post-adoption → disengagement/discontinuance trajectories and to identify disengagement triggers; and (3) where feasible, analysis of organizational artifacts (AI use policies, quality standards, security and confidentiality requirements).

A central condition for such research is strict adherence to voluntary participation, anonymization, and confidentiality, alongside explicit safeguards preventing the use of study outputs for sanctions against individual employees or teams.

EXPECTED CONTRIBUTIONS

From a theoretical perspective, the proposed model advances AI adoption research in three ways. First, it shifts attention away from a binary "adopted/not adopted" framing toward a more differentiated typology of behavioral states, ranging from enthusiasm and sustained active use to superficial compliance and covert resistance. Second, incorporating trust in AI and cognitive load into TAM and TOE foregrounds the fact that engineering teams operate under high cognitive density, where any new tool must not only deliver utility but must preserve engineers' mental capacity and stability in complex work environments [1], [5]. Third, emphasizing disengagement triggers builds a conceptual bridge between research on digital transformation, organizational behavior, and engineering management, enabling more precise propositions about which organizational practices can prevent disengagement from AI or, conversely, intensify it.

From a practical perspective, the model directs leaders of engineering units to act across multiple dimensions simultaneously. Strengthening perceived usefulness requires more than communicating the benefits of AI; it requires co-designing, together with engineers, use scenarios in which AI genuinely removes process bottlenecks rather than creating new ones. Increasing trust in AI implies algorithmic transparency where feasible, clear rules for validation and for human–AI joint decision-making, and training that explicitly addresses the cognitive and emotional conditions of interacting with AI tools [1; 5; 8]. Addressing organizational influence entails developing a coherent AI strategy at the unit level, allocating resources for training and tool configuration, and aligning AI use with incentive and evaluation systems in a way that does not erode engineers' perceptions of fairness and autonomy.

CONCLUSION

The literature review supports the position that organizational barriers to AI implementation and sustained use in engineering workflows arise at the intersection of individual perceptions of perceived usefulness and trust in AI, a set of technical, cognitive, emotional, and process-related difficulties, and organizational influence shaped by culture, leadership and training practices, incentive structures, quality standards, and security/confidentiality requirements.

The proposed conceptual model integrates TAM and TOE with trust in AI, cognitive load, and disengagement triggers, enabling analysis of post-adoption trajectories that move beyond "acceptance/non-acceptance" and extend from active use to nominal compliance, covert resistance, and discontinuance. The model provides a basis for a planned mixed-methods empirical assessment (including an SDLC case using the Stack Overflow Developer Survey combined with a new qualitative survey/interview component) and can support both diagnosis of disengagement drivers and the design of organizational interventions aimed at increasing the durability of AI-enabled work practices.

Future research can test the proposed propositions across different types of engineering teams (software development, hardware design, operations and maintenance, R&D), compare industry settings and national environments, and develop and evaluate concrete managerial interventions aimed at reducing disengagement triggers and strengthening trust in AI. Over time, this line of work can not only improve the effectiveness of AI initiatives but also enhance their stability and alignment with the values and expectations of engineering professionals.

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