Universiteit Leiden

ICT in Business and the Public Sector

Impact of Generative AI on Teamwork: Opportunities and Challenges- A Systematic Literature Review

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Date: 26/08/2025

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MASTER'S THESIS

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Abstract

Background: The rapid rise of Generative Artificial Intelligence (GenAI) is reshaping team dynamics in modern workplaces, affecting communication, coordination, creativity, decision-making, and engagement. Tools such as ChatGPT and GitHub Copilot are increasingly integrated into professional workflows, yet their systemic influence on collaborative processes remains underexplored, with most prior research focusing on individuals or specific tasks.

Aim: This thesis examines how GenAI affects teamwork, analyzing benefits, challenges, and limitations across key dimensions to provide both theoretical insight and practical guidance for responsible integration.

Method: A Systematic Literature Review (SLR) was conducted using the PRISMA framework, synthesizing findings from 31 peer-reviewed studies (2022–2025) selected for relevance, methodological rigor, and focus on team-based settings.

Results: We identified eight core teamwork dimensions: communication and shared understanding, coordination and task division, trust and cohesion, creativity and innovation, decision-making and problem-solving, learning and feedback, role definition and team structure, and engagement and inclusivity. We found that GenAI improves efficiency through automation, accelerates ideation, and fosters inclusion by enabling low-pressure participation, particularly for diverse teams. However, it also risks reducing interpersonal interaction, creating role ambiguity, fostering overreliance, and introducing ethical issues such as bias and opacity, which can erode trust.

Conclusion: We found that Generative AI enhances team communication, accelerates ideation, promotes inclusion, and improves efficiency through automation, particularly in diverse and software development teams. However, it also disrupts traditional team models by reducing interpersonal interaction, creating role ambiguity, fostering overreliance, and introducing ethical complexities like bias and opacity, which can erode trust. Based on these findings, we propose practical strategies to address these challenges: designing human-centered collaborative interfaces to sustain interpersonal engagement, implementing transparent practices by disclosing AI-generated content to maintain trust, and providing AI literacy training to ensure equitable access and foster inclusive participation.

Keywords: Generative AI, teamwork, collaboration, large language models, human-AI interaction, trust, team dynamics, software development, responsible AI, engagement, inclusivity

Acknowledgements

I express my deepest gratitude to Dr. Christoph Stettina for his academic supervision, insightful feedback, and unwavering encouragement, which were instrumental to this thesis's success. I am also grateful to Dr. Joost Visser for his constructive criticism and valuable suggestions, which significantly enhanced the depth and clarity of my work.

My heartfelt thanks go to my father and my family, whose unwavering support, love, and prayers have been a continuous source of strength throughout this journey. Your belief in me has kept me grounded and determined at every step.

Above all, I thank God, whose guidance and mercy illuminated my path. Without divine grace, none of this would have been possible.

This work is dedicated to the memory of my beloved mother. Her love, resilience, and sacrifices remain a lasting source of inspiration. May her soul rest in eternal peace.

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1. Introduction

In recent years, the rapid advancement of digital technologies such as artificial intelligence (AI), cloud computing, data analytics, robotics, and the Internet of Things (IoT) has reshaped how work is structured and executed across industries (Rodríguez-Lluesma et al., 2020). Among these, AI has emerged as a transformative force that is redefining how individuals and teams communicate, coordinate, and make decisions in collaborative environments (Zhang et al., 2023).

One of the most disruptive innovations within AI is Generative Artificial Intelligence (GenAI), a class of technologies capable of generating text, code, images, and other content based on large datasets, typically through Large Language Models (LLMs) (Mayer et al., 2025). Tools like ChatGPT and GitHub Copilot are being increasingly integrated into professional workflows, playing a role in various tasks such as content creation, software programming, and real-time collaboration (Dwivedi et al. 2023). These technologies are beginning to influence fundamental aspects of teamwork and group-based problem-solving (Sengar et al., 2024).

Meanwhile, teamwork is a cornerstone of organizational success, particularly in areas like software engineering and cross-functional innovation teams (Salas et al., 2005). Effective teams generally align on their goals, roles, and responsibilities, and rely on continuous coordination and mutual accountability to succeed (Mathieu et al., 2008). The introduction of GenAI into this context has led to new forms of human–AI collaboration, where AI tools are woven into team communication, creativity, and decision-making processes (Ulfsnes et al., 2024). This integration introduces both opportunities and challenges particularly in balancing automation with human agency and maintaining trust and psychological safety (Seeber et al., 2020).

1.1 Problem statement

Although GenAI technologies are widely adopted in various settings, much of the existing literature focuses on narrow or isolated effects such as individual productivity or decision support. There is a noticeable gap in comprehensive analyses that consider GenAI's broader, systemic influence on team dynamics as a whole. While some studies explore specific aspects like creativity or trust, few offer a synthesized perspective that connects these insights into a coherent understanding. This lack of integration limits both theoretical development and practical guidance for organizations. Therefore, a systematic and holistic review of GenAI’s impact on teamwork is urgently needed.

1.2 Research Questions

To address this gap, this study conducts a Systematic Literature Review (SLR) to critically examine and synthesize empirical findings on the role of GenAI in team-based settings. The review focuses on identifying how GenAI influences different dimensions of teamwork and is guided by the following research questions:

RQ1: Which dimensions of teamwork are influenced by the integration of GenAI, and how are these effects characterized?

RQ2: What benefits, limitations, and challenges are reported in the literature regarding the use of GenAI tools in team workflows?

1.3 Thesis Outline

This thesis is organized into six chapters:

- Chapter 1 – Introduction: outlines the research background, motivation, and research questions.
- Chapter 2 – Background: reviews key theories of teamwork, the evolution of Generative AI, and models of human–AI collaboration.
- Chapter 3 – Review Method: explains the systematic literature review process, including selection criteria, search strategy, and data analysis.
- Chapter 4 – Results: presents findings from studies, highlighting how GenAI affects various teamwork dimensions and outlining its benefits and challenges.
- Chapter 5 – Discussion: interprets the results in light of existing theories and identifies theoretical and practical implications, as well as research gaps.
- Chapter 6 – Conclusion: summarizes key insights and offers recommendations for future research on GenAI in team contexts.

2. Background

2.1 Teamwork and Collaboration

Teamwork involves the coordinated activity of individuals working interdependently toward shared objectives. It is the process through which team members collaborate to achieve task goals, translating team inputs into outputs such as effectiveness and satisfaction (Driskell et al., 2018). Essential features of effective teams include clearly defined goals, task interdependence, ongoing interaction, and boundary management (Xyrichis & Ream, 2008).

Although often used interchangeably, the terms teamwork and collaboration are conceptually distinct. Collaboration is a broader term that may involve information sharing or consultation without requiring strong interdependence (Xyrichis & Ream, 2008). For instance, a doctor might seek a nurse’s input when making clinical decisions (Xyrichis & Ream, 2008). While this reflects collaboration, it does not necessarily constitute teamwork unless both are jointly accountable for the outcome (Xyrichis & Ream, 2008). In contrast, teamwork is characterized by coordinated adjustments among members, a shared sense of responsibility, and joint control over how tasks are carried out. (Driskell et al., 2018).

Recognizing the distinction between collaboration and teamwork is crucial for accurately assessing GenAI’s impact on team processes. In collaborative settings, GenAI primarily enhances information sharing and individual productivity (e.g., using ChatGPT for brainstorming). In contrast, in teamwork, it can fundamentally reshape core dynamics by influencing communication, trust, coordination, and role clarity. Conflating these contexts risks misjudging GenAI’s effects either overestimating its impact on straightforward collaborative tasks or underestimating its transformative potential in highly interdependent teams.

2.1.1 Models and Theories of Teamwork

The study of teamwork has produced a range of models that explain how teams form, function, and succeed. These frameworks offer essential insights for analyzing how technologies like generative AI may influence team processes, roles, and performance.

Tuckman's Team Development Model: This model outlines five sequential stages of team development: Forming, Storming, Norming, Performing, and Adjourning (Tuckman & Jensen, 1977). In the Forming stage, members become acquainted and establish ground rules. Storming involves conflicts due to differing perspectives, which, if resolved, lead to the Norming stage, marked by growing trust and shared norms. The Performing stage reflects peak efficiency, while the Adjourning stage involves disbanding the team after achieving its goals (Tuckman & Jensen, 1977)

McGrath's Input–Process–Output (IPO) Model: This model provides a systems-based view of teamwork, proposing that team performance emerges from the interaction of inputs such as member skills and resources, processes such as coordination and decision-making, and outputs such as task completion and satisfaction (Kozlowski & Ilgen, 2006).

Hackman's Team Effectiveness Model: This model is based on the idea that a team's effectiveness is measured not only by its final results but also by the quality of its teamwork process and the growth and satisfaction of its members. It emphasizes delivering high-quality output that meets stakeholders' needs, maintaining or improving the team's ability to collaborate effectively in the future, and ensuring members' satisfaction, motivation, and learning. The model also identifies five key conditions for team success: having a real team with clearly defined boundaries, a clear and challenging purpose, a well-structured team design with the right mix of skills and effective norms, sufficient organizational support such as resources, training, and rewards, and a capable leader or coach to provide guidance and feedback (Cavanaugh et al., 2021).

GRPI Model: This model comprising Goals, Roles, Processes, and Interpersonal Relations offers a structured, sequential, and interconnected approach for assessing team effectiveness. According to this model, a team should first articulate its overarching objectives with clarity, then define and assign specific responsibilities to each member. Once roles are established, the focus shifts to developing clear processes, including the workflows and decision-making strategies that support task completion. The final component highlights the importance of healthy interpersonal dynamics, such as effective communication, collaboration, mutual trust, and constructive conflict resolution, which are critical for sustaining high performance (Karabiyik et al., 2020).

Lencioni's Five Dysfunctions of a Team model: This model presents a hierarchical view of barriers that hinder team effectiveness. At its base is a lack of trust, which prevents open communication and psychological safety. This leads to a fear of conflict, limiting productive dialogue. In turn, the absence of conflict reduces commitment to shared goals, resulting in a lack of accountability and, ultimately, inattention to results (Chiejina, 2023).

2.2 Generative Artificial Intelligence (GenAI)

Artificial Intelligence (AI) refers to computational systems designed to perform tasks that typically require human intelligence, such as reasoning, decision-making, and language processing (Russell & Norvig, 2003). For the purposes of this review, the focus is on Artificial Narrow Intelligence (ANI), which encompasses specialized systems designed for specific tasks and currently represents the most common application of AI in organizational teams (Saghiri et al., 2022).

A significant development within ANI is the rise of GenAI models, which are capable of producing original content such as text, code, images, or audio rather than merely analyzing existing data (Gozalo-Brizuela & Garrido-Merchán, 2023). These models, including LLMs, GANs, and AI-powered coding assistants, are increasingly integrated into workplace environments to automate tasks, enhance creativity, and support decision-making (Holzner et al., 2025).

Unlike earlier rule-based systems, which rely on predefined rules with limited autonomy, Generative AI tools operate with high autonomy, often generating human-like outputs with minimal input. Their relevance to teamwork lies in their ability to augment human capabilities, boost productivity, and reshape team interactions and workflows (Manduchi et al., 2025).

2.2.1. Types of AI Relevant to Team Settings

Several AI technologies are particularly relevant to collaborative work environments.

Large Language Models (LLMs) and Conversational Agents

Serving as the backbone of many generative AI applications, LLMs are capable of generating coherent, context-aware text that supports tasks such as summarization, documentation, ideation, and content generation, thereby enhancing both productivity and creativity (Gozalo-Brizuela & Garrido-Merchán, 2023). When deployed as chatbots or conversational agents (e.g., ChatGPT), these models facilitate real-time dialogue, provide information, support coding or calculations, and assist with writing tasks. Acting as on-demand knowledge assistants, they help reduce communication bottlenecks and improve collaborative efficiency (Subramonyam et al., 2025).

Collaborative Augmentation Systems

AI copilots and embedded assistants are integrated into domains such as software development, design, and project management, where they proactively deliver relevant suggestions or generate content in response to user input. By harnessing the complementary strengths of automation and human judgment, these systems aim to enhance productivity, stimulate creativity, and improve the quality of decision-making, while maintaining usability, safety, and core human values (Shneiderman, 2020).

Decision-Support Systems

Decision-support systems enables the analysis of large datasets and the detection of hidden patterns, supporting complex decision-making in teams. In collaborative environments, particularly in high-risk or uncertain situations, this technology enhances the speed and accuracy of decisions by providing predictive analytics and precise risk assessments. The integration of hybrid human–AI decision making models combines human judgment with machine processing power, resulting in more informed choices and faster responses when facing organizational challenge (Joshi, 2025).

2.3. Human-AI Collaboration

Artificial intelligence (AI) is transforming team dynamics by evolving from a passive tool to an active teammate capable of reasoning, adaptive planning, and decision-making (Berretta et al., 2023). This shift leverages the complementary strengths of humans and AI, fostering adaptability, resilience, and enhanced performance through a socio-technical approach (Lou et al., 2025). Frameworks such as Human-Centered AI (HCAI), Intelligence Augmentation (IA), and Human-Autonomy Teaming (HAT) guide this integration, addressing design, enhancement, and coordination in human-AI teaming. Below, we explore their roles and implications.

2.3.1. Human-Centered AI (HCAI)

Human-Centered AI (HCAI) is a design approach for AI systems that puts human welfare, societal well-being, and alignment with human values, needs, and capabilities at the forefront. It incorporates human-centered design (HCD) principles to tackle AI's inherent complexity, autonomy, and adaptive nature, all while promoting ethical alignment, transparency, and accountability (Schmager et al., 2025). Its core elements encompass purposes such as enhancing human abilities, supporting AI autonomy, and automating tasks; values like ethics, safety, and performance to minimize risks; and properties including oversight, comprehension, and integrity to boost explainability and user control (Schmager et al., 2025). In fields like semi-autonomous driving, HCAI uses large-scale naturalistic data to examine driver behavior, helping to grasp attention distribution, interventions, and trust in automation ultimately enhancing shared autonomy and cutting down on errors (Fridman et al., 2019). Likewise, in healthcare, it improves explainability in AI diagnostics, allowing humans to interpret and step in as needed, which builds trust and supports smooth team collaboration (Schmager et al., 2025).

2.3.2. Intelligence Augmentation (IA)

Intelligence Augmentation (IA) refers to the use of technology to enhance and support human cognitive abilities rather than replacing them. Unlike Artificial Intelligence (AI), which aims to simulate or even substitute human cognitive functions, IA focuses on collaboration between humans and machines to improve decision-making, creativity, and productivity. In IA, the human remains at the center of the human-computer interaction, while systems act as tools that process large datasets and apply machine learning algorithms to assist humans in performing tasks more effectively. Practical examples of IA include augmented reality glasses, virtual assistants, and collaborative robots, all designed to increase efficiency while enabling humans to focus on complex, creative, and context-driven decisions (Hassani et al., 2020).

2.3.3. Human–Autonomy Teaming (HAT)

Human–Autonomy Teaming (HAT) refers to the collaboration between humans and autonomous systems, where both parties work complementarily to enhance performance and decision-making in complex environments. This collaboration raises significant ethical challenges, as intelligent systems may face situations requiring morally sensitive decisions, such as emergency response or life-saving operations. Ensuring transparency, accountability, fairness, and maintaining human oversight is essential for the societal acceptance and successful implementation of HAT technologies (Pflanzer et al., 2022).

2.4 Impact of Generative AI on Teamwork Dimensions

The emergence of generative AI is redefining the landscape of team collaboration by introducing capabilities that extend beyond traditional automation. Unlike rule-based systems, GenAI tools such as large language models, code assistants, and AI-driven design platforms can autonomously generate content, engage in dialogue, and contribute to cognitive tasks (Russell & Norvig, 2003). These functionalities position GenAI as a dynamic partner in team settings, potentially transforming how teams communicate, coordinate, and innovate (Seeber et al., 2020).

The following explores how GenAI influences key dimensions of teamwork, such as communication, trust, learning, creativity, decision-making, and role allocation.

2.4.1 Communication and Coordination

Effective communication and coordination are cornerstones of teamwork, facilitating information exchange, task alignment, and shared understanding (Driskell et al., 2018). GenAI has the potential to enhance these processes by automating routine tasks such as meeting summarization, language translation, and report drafting, thereby streamlining workflows and reducing cognitive load (Shneiderman, 2020). In diverse or geographically dispersed teams, GenAI's ability to provide real-time translation and transcription can bridge linguistic and temporal barriers, fostering more inclusive collaboration (Dwivedi et al., 2023).

Moreover, GenAI can analyze team interaction patterns to identify inefficiencies, such as redundant exchanges or communication bottlenecks, aligning with the process optimization focus of the GRPI framework (Karabiyik et al., 2020). By accelerating information flow, GenAI may enable teams to respond more swiftly to dynamic demands, enhancing overall efficiency.

However, these advancements come with risks. Overreliance on AI-mediated communication may depersonalize interactions, diminishing emotional nuance and nonverbal cues critical for building relational trust (Seeber et al., 2020).

2.4.2 Trust and Reliance

Trust is a foundational element of teamwork, enabling shared accountability and psychological safety (Salas et al., 2005). In GenAI-integrated teams, trust extends beyond human teammates to include AI systems, which can serve as reliable sources of objective insights when designed transparently (Johnson & Vera, 2019). By reducing cognitive workload and providing data-driven recommendations, GenAI may strengthen confidence in team processes, particularly in complex or high-stakes tasks (Shneiderman, 2020).

Yet, building trust in GenAI is challenging due to the opacity of many models, often described as "black boxes" (Dignum, 2017). Lack of explainability can foster skepticism, especially when AI outputs are inconsistent or difficult to interpret, potentially destabilizing team cohesion as outlined in Lencioni's model (Chiejina, 2023). Conversely, uncritical reliance on GenAI outputs risks eroding human judgment, creating a dependency that could undermine accountability (Amershi et al., 2019).

2.4.3 Knowledge Sharing and Learning

Knowledge sharing underpins team effectiveness by enabling collective expertise and adaptive learning (Mathieu et al., 2008). GenAI can enhance these processes by synthesizing vast datasets, recommending relevant resources, and providing just-in-time learning support (Samid, 2021). By facilitating rapid access to information, GenAI may reduce knowledge gaps, streamline onboarding, and support the development of shared mental models, a key component of team cognition theory (Wegner, 1987).

However, GenAI's reliance on aggregated data may prioritize mainstream perspectives, potentially marginalizing diverse or novel insights (Saghiri et al., 2022). Overuse could also discourage critical inquiry and peer-to-peer knowledge exchange, weakening the collaborative learning processes central to Hackman's effectiveness model (Cavanaugh et al., 2021).

2.4.4 Creativity and Innovation

Creativity drives innovation in teams, particularly in tasks requiring problem-solving and ideation (Anderson et al., 2014). GenAI can augment these processes by generating diverse content such as text, designs, or code offering teams a wealth of starting points to spark new ideas (Gozalo-Brizuela & Garrido-Merchán, 2023). By reducing the cognitive burden of ideation, GenAI aligns with intelligence augmentation principles, enabling teams to explore novel solutions and iterate rapidly (Samid, 2021).

Nevertheless, GenAI's pattern-based outputs may lack originality or cultural sensitivity, risking homogenized results that stifle true innovation (McCormack et al., 2020). Teams overly reliant on GenAI may also undervalue human intuition and contextual judgment, which are critical for refining creative outputs (Shneiderman, 2020).

2.4.5 Decision-Making and Problem-Solving

Decision-making is a core team function, requiring the integration of information and consensus-building (Kozlowski & Ilgen, 2006). GenAI supports this by synthesizing data, generating predictive insights, and simulating scenarios, potentially enhancing decision speed and accuracy (Russell & Norvig, 2003).

However, GenAI's influence raises concerns about accountability and bias. Opaque decision-making processes can obscure responsibility, particularly when errors occur, challenging the shared accountability emphasized in team effectiveness models (Cavanaugh et al., 2021). Biases in training data may also lead to inequitable outcomes, necessitating critical evaluation (Dignum, 2017). Teams must maintain human-centered decision-making, using GenAI as a supportive tool while retaining collective ownership over outcomes (Berretta et al., 2023).

2.4.6 Role Allocation and Work Distribution

Clear roles and equitable task distribution are vital for team performance (Hackman's Team Effectiveness Model; Cavanaugh et al., 2021). GenAI can optimize these by analyzing team skills and workloads to recommend dynamic role assignments, enhancing flexibility in response to changing demands (Dwivedi et al., 2023). By automating routine tasks, GenAI allows team members to focus on higher-value activities, potentially boosting engagement and productivity (Shneiderman, 2020).

However, over-automation risks marginalizing team members, reducing opportunities for skill development and meaningful contribution (Seeber et al., 2020). AI-driven decisions may also reinforce power imbalances if not implemented transparently, undermining participatory dynamics (Saghiri et al., 2022).

In summary, the convergence of teamwork theory, emerging models of human–AI collaboration, and the transformative capabilities of Generative AI underscores a profound shift in how teams function, communicate, and innovate. While GenAI offers new pathways for enhancing productivity, coordination, and creativity, its integration into team workflows also raises unresolved tensions surrounding trust, role clarity, shared understanding, and ethical accountability. Current research often addresses these issues in fragmented or conceptual ways, lacking a synthesized, evidence-based understanding of how GenAI shapes team dynamics in practice. This fragmentation leaves both theoretical models and organizational strategies without clear guidance for navigating human–AI collaboration.

To address this critical gap, the following chapter outlines the methodological framework of this study, detailing the systematic literature review (SLR) conducted to rigorously examine existing empirical work at the intersection of GenAI and teamwork.

3. Review Method

To systematically investigate the research questions posed in this study, a Systematic Literature Review (SLR) was conducted in accordance with well-established methodological guidelines in software engineering and information systems (Kitchenham & Charters, 2007; Webster & Watson, 2002). As a research strategy, SLRs play a critical role in consolidating cumulative knowledge by mapping core concepts, uncovering theoretical patterns, and identifying research gaps within a given domain (Okoli 2015; Petticrew & Roberts, 2006).

In addition, the review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol (Page et al., 2021), which offers a structured and transparent framework for conducting and reporting systematic reviews. The PRISMA guidelines helped ensure methodological clarity through standardized steps including study identification, screening, eligibility evaluation, and final inclusion.

By combining the methodological rigor of SLRs with the reporting transparency of PRISMA, this review enabled a critical and structured synthesis of existing literature on the role of Generative Artificial Intelligence (GenAI) in teamwork particularly in software development settings while also surfacing important knowledge gaps that warrant further empirical and theoretical investigation.

3.1 Protocol development

The review protocol was developed to ensure methodological thoroughness and transparency in alignment with established SLR guidelines from Kitchenham and Charters (2007) and reporting standards from PRISMA (Page et al., 2021). The process was divided into three main phases: (1) Planning the Review, (2) Conducting the Review, and (3) Reporting the Review, as illustrated in Figure 1.

In the planning phase, we identified literature gaps, formulated two research questions, and designed a structured search strategy (Section 3.4). In the conducting phase, we applied inclusion and exclusion criteria (Section 3.3), assessed study quality using a 10-point checklist, and extracted and synthesized data based on thematic relevance. The reporting phase involved presenting findings, validating results for consistency through iterative data checks and alignment with research questions, and preparing a structured synthesis to address study objectives.

This protocol ensured consistency across all steps of the review and provided a replicable framework for future research in the intersection of Generative AI and teamwork

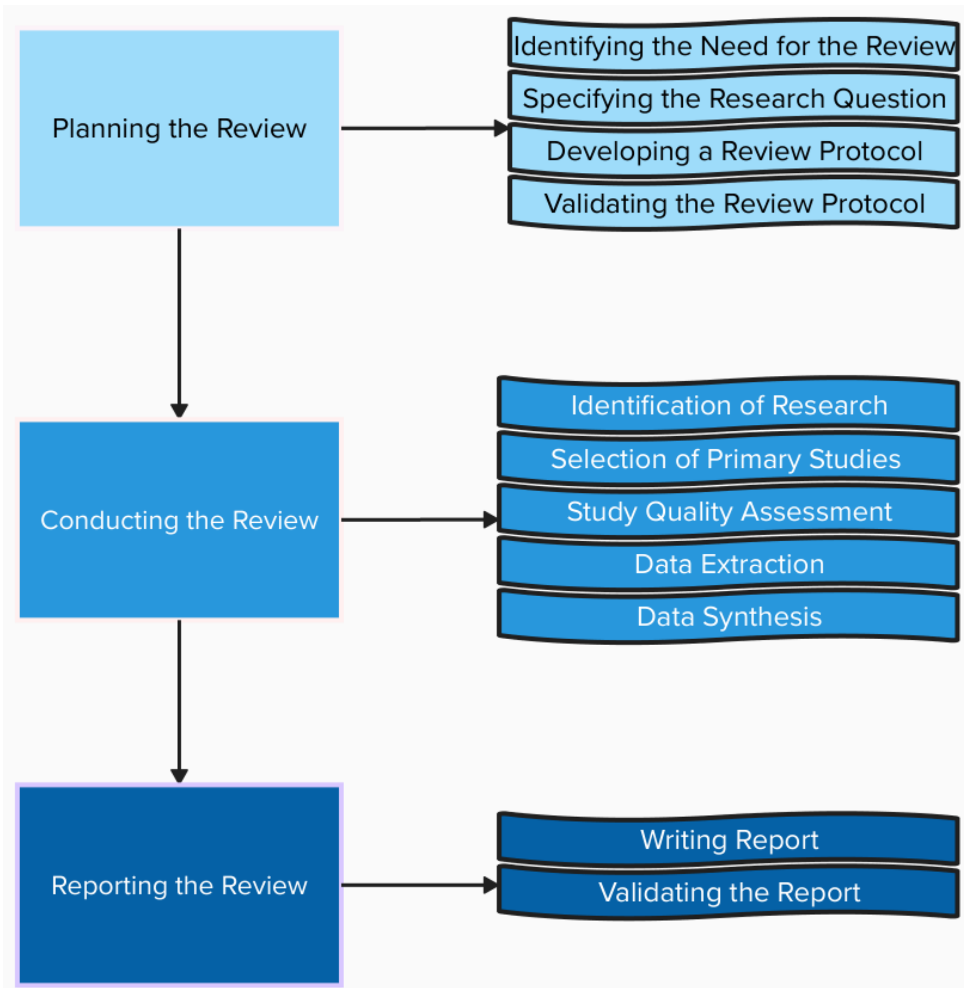

Figure 1. Systematic Literature Review Protocol

3.2 Inclusion and Exclusion Criteria

To ensure methodological rigor and alignment with the study's objectives, inclusion and exclusion criteria were developed based on established SLR guidelines (Kitchenham & Charters, 2007; PRISMA, Page et al., 2021). These criteria were designed to identify studies that are both conceptually relevant and empirically sound.

Inclusion focused on peer-reviewed publications in English, published between January 2022 and June 2025, that examined the use of Generative AI (e.g., LLMs, ChatGPT, Copilot) in team-based contexts, particularly regarding collaboration, decision-making, and creativity.

The start date of January 2022 was chosen as peer-reviewed studies on early GenAI tools, such as Codex and GitHub Copilot (released in mid-2021), began emerging in early 2022 due to the time required for peer-review processes.

Exclusion criteria ruled out non-peer-reviewed materials, individually focused studies, outdated sources, and inaccessible or duplicate records. The full criteria are summarized in Table 1.

Criteria	**Sub-Criteria**	**Description**
Inclusion	Publication Type	Peer-reviewed journal articles; Academic conference papers and workshops
	Subject Matter	Studies examining the use of Generative AI technologies (e.g., ChatGPT, LLMs) in team-based environments. Focus on teamwork processes such as collaboration, communication, creativity
	Study Type	Empirical (quantitative, qualitative, or mixed methods) or conceptual research with a clear theoretical framework
	Time Frame	Published in English between January 2022 and June 2025
	Access	Open access or accessible through institutional subscriptions
Exclusion	Non-Peer-Reviewed Material	Blogs, white papers, opinion pieces, grey literature
	Irrelevant Focus	Studies not focused on Generative AI unrelated to teamwork or collaborative contexts Focus solely on individual productivity , lacking team-level analysis
	Outdated Research	Published before 2022
	Inaccessible or Duplicate Material	Sources inaccessible due to paywalls or duplicates (e.g., preprint and final version)

Table 1. Inclusion and Exclusion Criteria

3.3 Data source and search strategy

To ensure a comprehensive and systematic exploration of the literature, the search strategy was designed to identify relevant studies at the intersection of generative AI and teamwork. Given the multidisciplinary nature of this topic spanning fields such as artificial intelligence, organizational behavior, software engineering, and human-computer interaction the search aimed to capture a diverse range of empirical and conceptual works. A combination of structured keyword searches and iterative pilot testing was employed to refine the search terms and maximize the relevance of retrieved articles. The focus was placed on recent literature, reflecting the rapid evolution and deployment of generative AI tools in collaborative and team-based contexts.

The automated search phase focused on Google Scholar, selected for its wide coverage of peer-reviewed articles and conference papers across disciplines such as computer science, software engineering, management, and human-computer interaction. Although Google Scholar lacks advanced filtering tools, its inclusivity makes it particularly useful for emerging multidisciplinary topics like GenAI in teamwork.

A series of pilot searches were conducted to refine keywords and determine the most relevant combinations. The final search string is shown in Table 2.

Field	**Details**
Search string	“Generative AI” AND “Teamwork” AND “Software Development”
Target for Search String	Title, abstract, and keywords
Data Sources	Google Scholar

Table 2. Search Terms and Parameters

Boolean operators (AND) were used to ensure that all articles included references to generative AI, teamwork, and a software or development context. Searches were limited to the period 2022 to 2025, to capture developments following the public release and adoption of GenAI tools such as ChatGPT.

All retrieved records were imported into Zotero for reference management. Duplicates, inaccessible entries, and irrelevant studies (e.g., those not involving team contexts or GenAI) were removed during the screening process, as detailed in Section 3.4.

3.4 Selection and Screening Process

To ensure that only the most relevant and high-quality studies were included in this review, a structured selection procedure was followed. The process involved multiple stages of filtering and evaluation, based on clearly defined criteria aligned with the focus of this research. This step was essential to maintain consistency and academic rigor throughout the review.

3.4.1 Initial Screening: Titles and Abstracts

The initial screening involved reviewing the titles and abstracts of all records retrieved during the search phase. Each entry was assessed to determine whether it addressed both generative AI technologies such as large language models and generative tools and aspects of teamwork including collaboration, communication, coordination, creativity, or decision-making. Items that did not align with these focal points, or were clearly outside the academic scope (e.g., opinion pieces, blog posts), were set aside.

3.4.2 In-Depth Review: Full Texts

Following the initial screening, the full texts of the remaining studies were obtained and examined thoroughly. Each study was evaluated based on a set of predefined criteria, including methodological robustness, relevance to team-level analysis, and focus on generative AI technologies. Studies that did not meet these standards for instance, those centered solely on individual use of AI or that lacked a clear research framework were excluded. Reasons for exclusion were carefully recorded to ensure transparency in the selection process.

This systematic, multi-stage filtering process ensured that only studies offering meaningful insights into the intersection of generative AI and teamwork were included in the final review. The number of records identified, screened, excluded, and finally included is summarized in the PRISMA flow diagram (Figure 2).

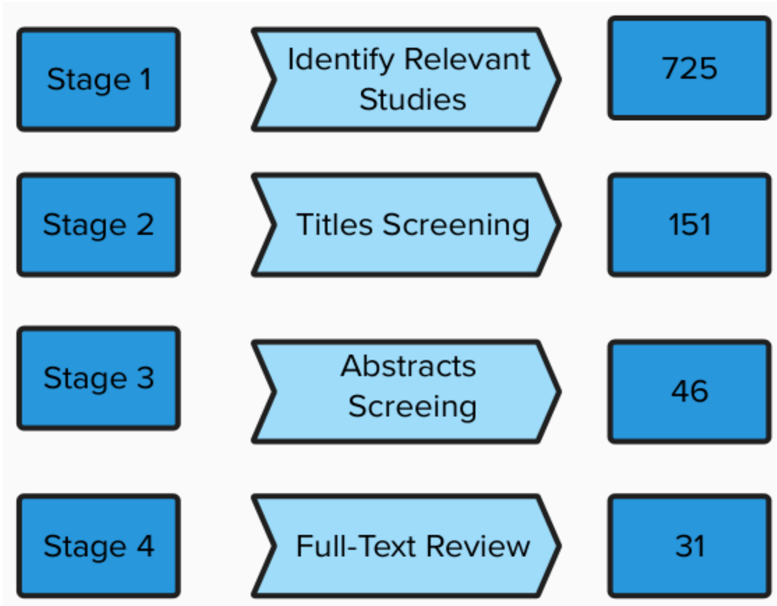

Figure 2. PRISMA Flow Diagram

3.5 Quality Assessment

To ensure the rigor and validity of the findings synthesized in this review, a structured quality assessment was conducted for all included studies. Following guidelines from Kitchenham and Charters (2007), the quality appraisal focused on methodological transparency, clarity of objectives, empirical grounding, and the appropriateness of conclusions. The primary purpose of this assessment was not to exclude studies, but rather to weigh the strength of evidence and support a more nuanced synthesis of the literature.

A quality assessment checklist was adapted based on previously published systematic reviews in software engineering (Bjørnson & Dingsøyr, 2008; Dybå & Dingsøyr, 2008).

The checklist covered criteria such as clarity of research objectives, methodological transparency, and use of appropriate data collection methods, relevance to GenAI and teamwork, and strength of findings. The full list of criteria is presented in Table 2.

No.	Criterion	Description
1	Clarity of Research Aims	Whether the study clearly defines its research objectives or questions.
2	Context Description	Whether the study describes the organizational, technological, or team context in which the research was conducted.
3	Methodological Rigor	Whether the data collection and analysis methods are appropriate and clearly explained (e.g., survey, case study, experiment, ethnography).
4	Empirical Evidence	Whether the study is supported by sufficient empirical data (e.g., participant numbers, tools used, data sources).
5	Theoretical Framework	Whether the study is guided by or contributes to a conceptual or theoretical model related to teamwork or AI.
6	Generative AI Relevance	Whether the use or discussion of Generative AI tools (e.g., LLMs, ChatGPT, Copilot) is central to the study.
7	Teamwork Contribution	Whether the study addresses at least one dimension of teamwork (e.g., collaboration, communication, coordination, performance).
8	Validity Discussion	Whether the authors discuss threats to validity, limitations, or biases in their study.
9	Clarity of Findings	Whether the findings are clearly presented and logically interpreted.
10	Relevance to Research Questions	Whether the findings contribute directly to answering this review’s central research questions.

Table 3. Quality Assessment Criteria

Each study was scored against these ten criteria using a 3-point scale (0 = not met, 0.5 = partially met, 1 = fully met), resulting in a total score ranging from 0 to 10. Studies scoring 5 or above were considered to have sufficient methodological quality to contribute meaningfully to the synthesis. The quality scores were not used to exclude studies unless a paper was missing essential information such that its findings could not be interpreted or verified. Instead, they helped inform the weighting of evidence during synthesis and analysis.

The assessment was conducted manually, supported by the literature review matrix developed in spreadsheet. This matrix captured detailed notes on each criterion for transparency. Studies with lower quality scores were analyzed cautiously, and any patterns found in such papers were cross-checked against higher-quality studies before inclusion in the thematic synthesis.

3.6 Data Extraction

To ensure a systematic and rigorous approach to data collection, a structured extraction framework was developed and applied consistently across all selected studies. The process was designed not only to collect methodological metadata but also to enable a detailed qualitative synthesis of how Generative AI (GenAI) impacts various dimensions of teamwork.

Data were manually extracted using a standardized Excel spreadsheet tailored to the aims of this review. Each article was reviewed in full, with close attention paid to both the abstract and main body of the text. As the review was conducted by a single researcher, additional steps were taken to ensure accuracy and reduce bias such as re-checking extracted entries and adhering strictly to the predefined inclusion and exclusion criteria.

The purpose of the extraction was twofold:

1. To document the methodological characteristics of each study, including research design, sample, context, and theoretical approach;
2. To capture substantive findings related to teamwork processes, such as communication, collaboration, decision-making, trust, creativity, and performance in the context of GenAI integration.

Emerging concepts and themes were identified during the extraction phase and iteratively tagged in a dedicated column. These tags were later grouped by content similarity to facilitate thematic analysis. Excel features such as filtering, sorting, conditional formatting, and commenting were used to support the identification of recurring patterns and to organize the data in a transparent and traceable way. Concept frequency and alignment with the research questions were tracked across entries to assist in theme development.

Although this process was conducted manually, the structured format of the spreadsheet provided a robust foundation for cross-study comparison and qualitative synthesis, which informed the thematic framework presented in Chapter 4.

A summary of the extracted fields is presented in Table 4 below.

Title	Full title of the study
Author(s)	The names of the authors
Year	Year of publication
Source	Publication Source (Journal, Proceedings, etc.)
Focus of Study	Main objective or research question addressed
Methodology	Research approach (Survey, Case study, etc)
Sample/Participants	Description of human subjects or data used
Key Findings	Summary of major outcomes and observations
Implications for Teamwork	How the results inform or guide teamwork

Table 4. Data Extraction Fields

3.7 Synthesis of Findings

To consolidate and interpret the results of the selected studies, a thematic synthesis approach was applied, building upon the structured data extracted in Section 3.6 (Kitchenham & Charters, 2007; Page et al., 2021). This approach, informed by meta-ethnographic synthesis principles (Noblit & Hare, 1988), aimed to identify overarching patterns and divergences across the literature through reciprocal translation (identifying similarities across studies) and refutational translation (examining contrasting findings due to methodological differences, team contexts, or AI tools used).

Key concepts and findings from each study were tabulated to facilitate systematic comparison. Data were iteratively categorized into thematic dimensions using structured tables, ensuring alignment with the study's research questions. This method enabled a comprehensive synthesis of how Generative AI influences teamwork, with results presented in Section 4.3

4. Results

This chapter presents the synthesized results of the literature review concerning the impact of GenAI on teamwork. The analysis includes empirical insights across diverse organizational and academic contexts, providing a comprehensive and academically rigorous account.

4.1 Overview of studies

This review synthesizes insights from 31 peer-reviewed studies (2022–2025) spanning computer science, software engineering, human–computer interaction, organizational behavior, and management, underscoring the topic's interdisciplinary scope. Together, these studies reveal the multifaceted impact of GenAI technologies such as ChatGPT, GitHub Copilot, and other LLM-powered tools on diverse dimensions of teamwork.

4.1.1 Temporal distribution of the studies

The temporal distribution of the studies reveals a noticeable increase in research output in 2024 and 2025, indicating growing scholarly attention following the widespread release of GenAI tools. Data are available through June 2025, representing only the first six months of the year, which is reflected in the final column of Figure 3.

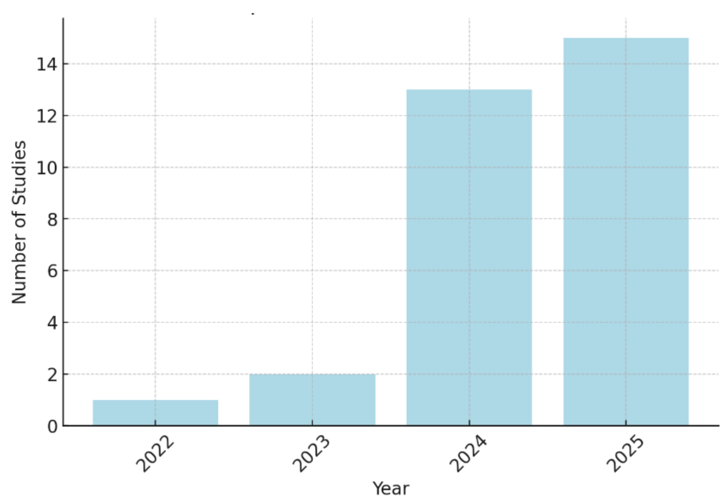

Figure 3**.** Temporal distribution of the studies

4.1.2 Geographic Distribution of Studies

The distribution of articles by continent shows that Europe and North America dominate research coverage, while Asia and multi-continental literature reviews receive moderate attention. In contrast, South America, Australia, and Africa are represented far less, highlighting a pronounced regional imbalance in research output. Articles were assigned to continents based on the locations where data were collected and the research was conducted, as detailed in Section 3.6. Literature reviews were classified as multi-continental studies because they draw on data from multiple regions. Notably, all articles associated with Asia originated from China and India, indicating a concentrated research focus within these countries. This imbalance may partly reflect differences in population size and wealth, as wealthier countries are likely to allocate more resources to scientific research; however, further analysis is needed to confirm this trend.

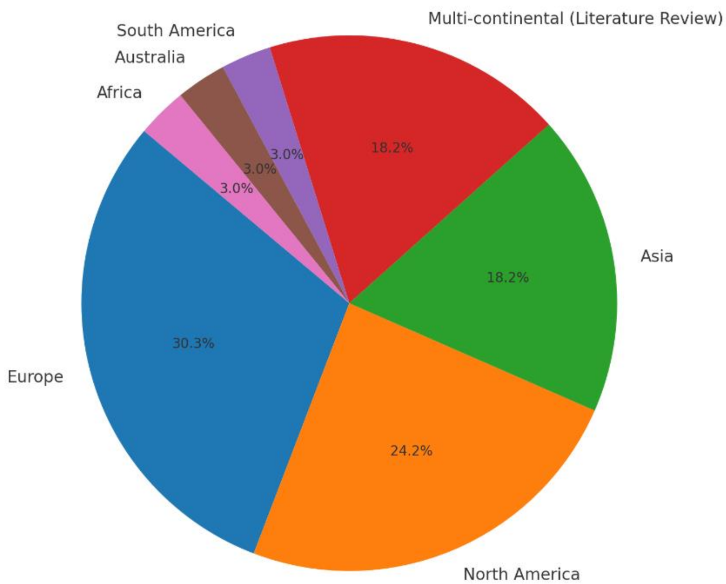

Figure 4. Geographic Distribution of Studies

4.1.3 Distribution of academic versus industrial affiliations

The comparison of academic and industrial affiliations reveals that 20 studies originate from academic institutions, 10 from the industrial sector, and 1 study involves both academic and industrial collaboration. This indicates a stronger representation of studies from the academic sector.

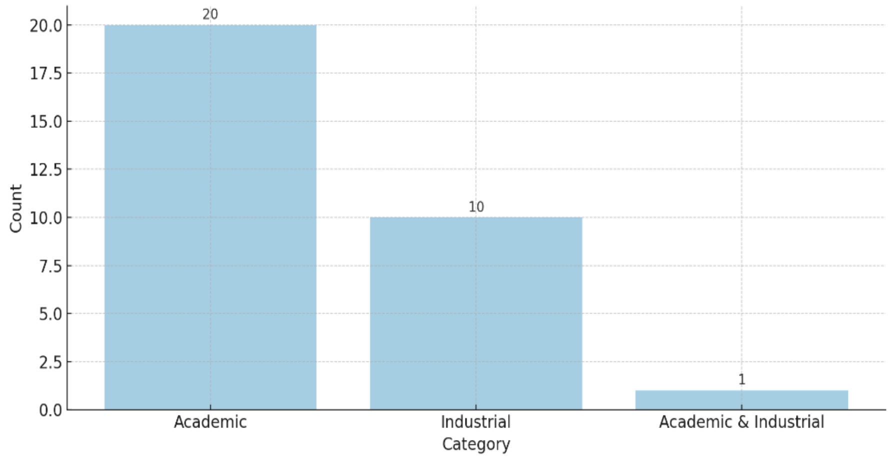

Figure 5. Distribution of academic versus industrial affiliations

4.1.4 Distribution of Studies by Publication Venue

The distribution of studies across publication venues shows a relatively balanced representation between academic journals (15 studies) and conference proceedings (14 studies), indicating that both venues are equally important for disseminating research in this area. In contrast, only a very small number of studies were published as book chapters (2), suggesting that edited volumes play a much less significant role in this field.

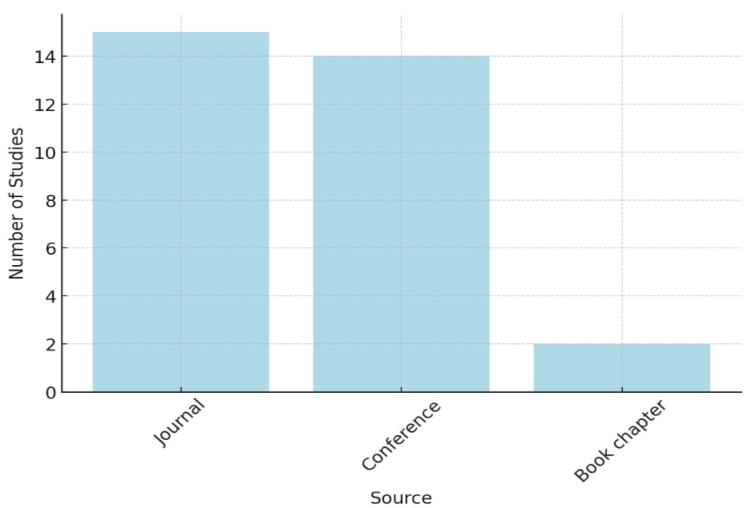

Figure 6. Distribution of Studies by Publication Source (2022-2025)

4.1.5 Distribution of Studies by duration

In terms of the distribution of articles according to their study duration, short-term studies are the most common, with 22 articles, indicating that researchers frequently choose studies with shorter timeframes. There are 7 articles categorized as "Not applicable (Review)," representing literature reviews without a defined study duration. Long-term studies are the least common, with only 2 articles.

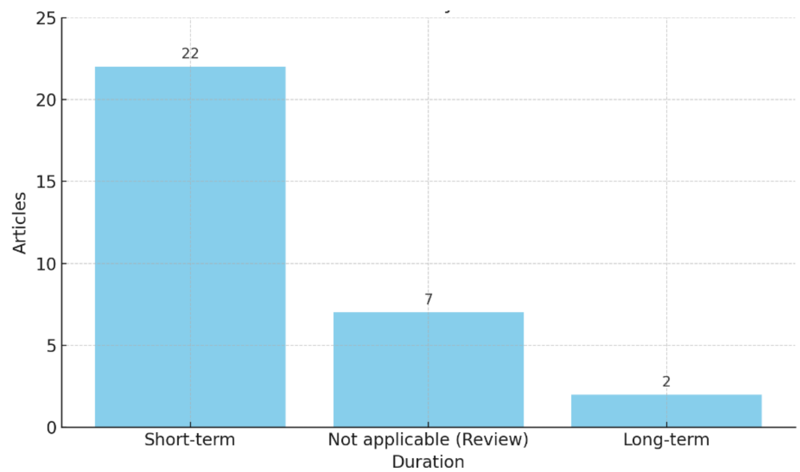

Figure **7.** Distribution of Studies by duration

4.2 Research Methods

The methodological distribution of the reviewed studies is presented in Figure 7. This diversity of approaches reflects the emerging and exploratory character of GenAI research in team-based contexts. The figure categorizes studies into five primary methodological types: Literature Review, Qualitative Study, Mixed Methods, Quantitative Study, and Design Science/System Design. The percentages represent the relative contribution of each category to the total number of articles.

Mixed Methods represents the largest share at 25.8% (8 articles), underscoring its versatility in combining qualitative and quantitative techniques. Literature Reviews follow with 22.6% (7 articles), emphasizing the reliance on systematic, narrative, selective, and bibliometric syntheses of existing knowledge. Qualitative Studies and Quantitative Studies each account for 19.4% (6 articles), illustrating a balance between exploratory, in-depth investigations (e.g., interviews, case studies) and statistically driven analyses (e.g., surveys, experiments). Finally, Design Science/System Design contributes the smallest share at 12.9% (4 articles), centering on system development and evaluation.

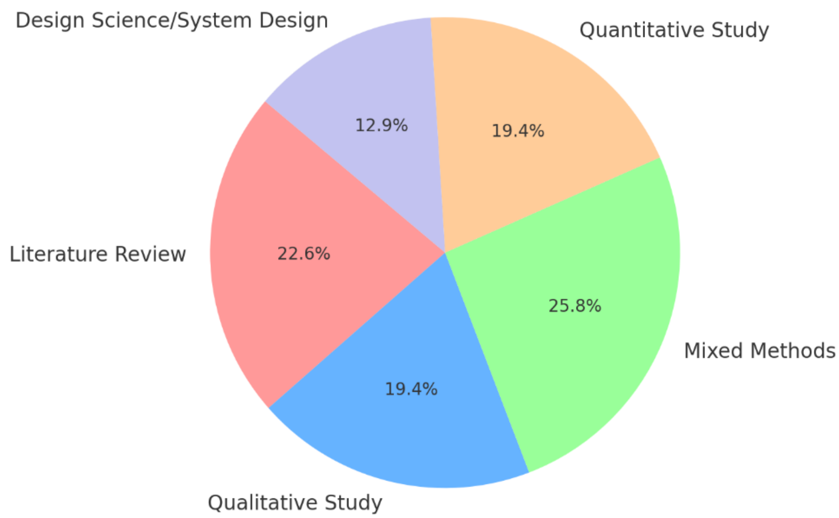

Figure 8. Distribution of Research Methodologies

Despite the variety of approaches, the current research landscape remains limited by the scarcity of longitudinal studies and large-scale industrial cases. The dominance of short-term, student-based research highlights a need for more ecologically valid and comparative investigations in real-world team settings.

4.3 RQ1: Which dimensions of teamwork are influenced by the integration of Generative AI, and how are these effects characterized?

The eight core dimensions of teamwork influenced by Generative AI were derived through a thematic synthesis of 31 peer-reviewed studies (2022–2025), following meta-ethnographic principles (Noblit & Hare, 1988). Key findings from each study were iteratively coded and grouped according to content similarity. This process involved initial descriptive coding, thematic grouping via reciprocal translation, and cross-validation with theoretical frameworks to ensure robustness. The resulting dimensions communication and shared understanding, coordination and task division, trust and team cohesion, creativity and innovation, decision-making and problem-solving, learning and feedback, role definition and team structure, and engagement and inclusive participation reflect both empirical insights and theoretical grounding. Figure 9 illustrates the distribution of scholarly attention across these dimensions, highlighting areas of focus and under-exploration.

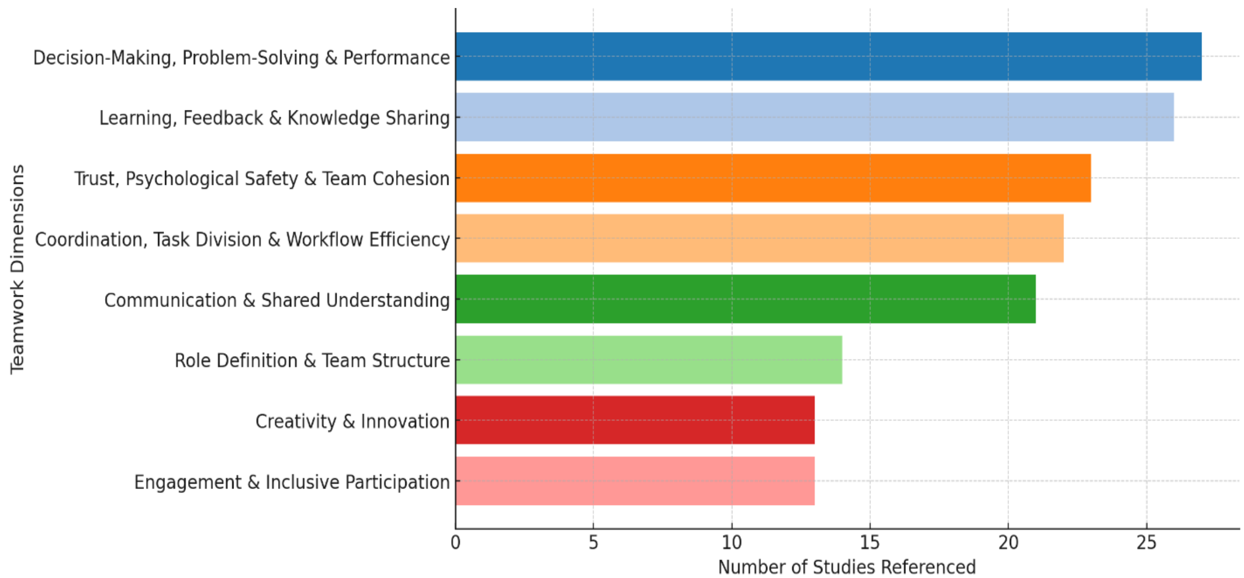

Figure 9: Generative AI's Effects on Teamwork Dimensions

Table 5 presents a structured overview of these dimensions, including concise descriptions and references to the studies from which they were derived. The subsequent section provides a deeper exploration of each dimension.

Teamwork Dimension	Main Findings	References
Communication & Shared Understanding	GenAI enhances clarity and reduces ambiguity in communication, but overreliance may reduce human-to-human interaction and weaken shared understanding.	S2, S3, S4, S5, S6, S9, S11, S12, S14, S15, S16, S17, S19, S20, S23, S24, S25, S26, S29, S30, S31
Coordination, Task Division & Workflow Efficiency	GenAI tools support structured task allocation and workflow visibility; however, inconsistent use can lead to fragmented coordination and misaligned responsibilities.	S3, S4, S5, S6, S7, S9, S10, S11, S13, S15, S16, S17, S19, S20, S21, S22, S24, S25, S26, S28, S30, S31
Trust, Psychological Safety & Team Cohesion	GenAI fosters psychological safety and trust by reducing anxiety and promoting transparency, yet may erode team cohesion if interpersonal interactions decline.	S1, S2, S3, S4, S5, S6, S7, S9, S10, S11, S14, S15, S17, S19, S20, S21, S22,S25, S26, S28, S29, S30
Creativity & Innovation	GenAI accelerates ideation and expands creative possibilities, but excessive dependence can lead to conformity, reduced originality, and diminished ownership.	S2, S3, S5, S6, S10, S11, S19, S22, S23, S24, S28, S30, S31
Decision-Making, Problem-Solving & Performance	GenAI improves team decision-making and performance by reducing cognitive load and aiding consensus, though risks include overconfidence and reduced critical thinking.	S1, S2, S3, S4, S5, S6, S7, S9, S10, S11, S12, S13, S14, S15, S16, S17, S20, S22, S23, S24, S25, S26, S27, S28, S29, S30, S31
Learning, Feedback & Knowledge Sharing	GenAI supports knowledge sharing and real-time feedback, but may discourage interpersonal learning and fragment collective understanding if used privately.	S1, S2, S3, S4, S5, S6, S7, S9, S10, S11, S12, S14, S15, S16, S17, S19, S20, S22, S23, S24, S25, S26, S27, S29, S30, S31
Role Definition & Team Structure	GenAI increases flexibility in role execution and can fill skill gaps, but often blurs responsibility, weakens accountability, and reduces explicit coordination.	S1, S3, S4, S6, S7, S11, S12, S13, S15, S21, S25, S26, S27, S30
Engagement & Inclusive Participation	GenAI enables low-pressure, inclusive contribution and equalizes participation, though hidden or uneven use can lead to disengagement and fairness concerns.	S4, S6, S7, S9, S11, S15, S16, S17, S22, S25, S27, S29

Table 5. Generative AI's Effects on Teamwork Dimensions

4.3.1 Communication and Shared Understanding

The integration of Generative AI into teamwork has produced both enabling effects and emerging tensions around communication and shared understanding. Many studies converge on the idea that GenAI can enhance clarity, reduce ambiguity, and foster mutual understanding particularly through improved documentation, semantic support, and accessible explanations. In programming contexts, for instance, GenAI helps teams align by making code more readable and facilitating comprehension across skill levels (Graf, 2025; Borghoff et al., 2025). Tools like ChatGPT and CoPrompt enable asynchronous, low-friction collaboration, allowing users to share context, clarify intentions, and reuse prior work without interrupting each other (Feng et al., 2024; Coutinho et al., 2024).

AI is also credited with reducing communication anxiety. In classroom or debate scenarios, it acts as a neutral party, helping participants express ideas more freely and converge on shared perspectives faster (Zhang et al., 2025). Interfaces like LADICA further support alignment by synchronizing spoken discussion with visual content (Zhang et al., 2025).

However, several studies raise concerns. A recurring theme is that reliance on GenAI may discourage human-to-human communication. Developers, for example, often prefer asking AI rather than teammates, which can lead to fragmented understanding and weakened interpersonal bonds (Ulfsnes et al., 2024; Wivestad et al., 2025). This shift risks creating isolated work patterns what one study metaphorically calls “islands of joy” where collaboration is efficient but disconnected (Wivestad et al., 2025). Others note that while AI reduces redundant questions, it can suppress meaningful dialogue essential to shared sensemaking (Mayer & Schwehn, 2025).

Overall, the effect of GenAI on communication and shared understanding appears contingent on its mode of integration. When used transparently and collaboratively, AI can scaffold mutual understanding and support inclusivity. When used individually and without coordination, it may erode the very communication it intends to support.

4.3.2 Coordination, Task Division and Workflow Efficiency

Generative AI has reshaped how teams coordinate actions, divide tasks, and manage workflows. A recurring finding across studies is that AI can enhance team-level coordination by supporting structured task distribution, synchronizing activities, and improving transparency. For example, AI-integrated systems like AgileGen and autonomous multi-agent frameworks assign distinct roles (e.g., planner, reviewer, developer) to AI agents in ways that mirror Agile team structures, enabling teams to manage tasks more systematically and reduce ambiguity in responsibilities (Zhang et al., 2024; Sanwal & Deva, 2024).

AI tools also support real-time coordination and task alignment during collaborative work. In LADICA, shared displays and goal decomposition features help teams visualize subtasks and monitor collective progress (Zhang et al., 2025). Similarly, CoPrompt structures multi-level prompts and version tracking, enabling asynchronous teams to manage dependencies and maintain clarity on evolving task structures (Feng et al., 2024). In organizational settings, AI facilitates cross-functional coordination, allowing teams to dynamically redistribute work across departments and external collaborators, particularly during complex innovation processes (Zheng et al., 2025).

Several educational and professional studies also show how GenAI helps maintain workflow visibility across teams. For instance, structured standup tools powered by AI allow mentors and team members to track each other's contributions and adjust task assignments to ensure balanced participation (Menezes et al., 2024).

Despite these benefits, some studies point to emerging coordination challenges. Reduced reliance on explicit communication, due to AI-mediated workflows, may lead to weakened collective synchronization. Teams risk falling into parallel work streams with limited integration what Ulfsnes et al. (2024) term “isomorphic team structures.” Additionally, inconsistent AI usage within teams can create imbalanced task division, where unclear expectations and uneven contribution levels undermine team cohesion and coordination (Graf, 2025).

In sum, GenAI offers strong support for team coordination and workflow structuring particularly when integrated into shared platforms and explicit team practices. However, without transparent, collaborative use, AI may inadvertently fragment coordination and reduce the collective alignment essential for effective teamwork.

4.3.3 Trust, Psychological Safety and Team Cohesion

The integration of Generative AI into team settings has produced mixed effects on trust, psychological safety, and cohesion. In many cases, AI contributes positively by creating psychologically safe environments where team members, especially novices or underrepresented individuals, feel more comfortable participating. AI's neutrality, lack of judgment, and immediate availability reduce social anxiety and lower the threshold for sharing ideas, asking questions, or making mistakes (Zhang et al., 2025; Feng et al., 2024; Menezes et al., 2024).

AI-enabled systems also enhance team transparency and accountability. Features such as visible contribution logs, prompt histories, and feedback mechanisms allow team members to monitor progress, align efforts, and foster confidence in each other's work (Feng et al., 2024; Menezes et al., 2024). In some contexts, emotionally expressive AI such as social robots helped reinforce cohesion through humor, empathy, and non-threatening interactions, increasing perceptions of trust and team bonding (Ren & Clement, 2024; Lasconi et al., 2022).

However, several studies caution against unintended social consequences. As teams increasingly rely on AI for support, they may interact less with one another, leading to weakened interpersonal ties and a decline in team cohesion (Wivestad et al., 2025; Mayer & Schwehn, 2025). Reduced peer interaction can erode trust and diminish the informal communication through which shared understanding and mutual support typically develop (Ulfsnes et al., 2024).

Ambiguity in the attribution of AI-generated work and uneven use of such tools present challenges. When the origin of outputs is unclear or when some team members rely heavily on AI while others do not, perceptions of fairness and engagement can suffer potentially leading to frustration or distrust (Graf, 2025; Mayer et al., 2024). Furthermore, framing AI as a “teammate” rather than a “tool” may intensify psychological pressure and reduce job security, especially when AI is assigned high responsibility in task execution (Flathmann et al., 2023).

Trust in AI systems themselves is shaped by factors such as explainability, role clarity, and perceived competence. Studies emphasize the importance of "appropriate reliance" on AI, where team members are encouraged to trust AI outputs without becoming dependent on them, maintaining room for critical evaluation and human judgment (Mayer et al., 2024; Wilkens et al., 2023).

In sum, GenAI can enhance psychological safety and trust in teams by reducing social barriers and supporting transparency. Yet without careful integration, it may disrupt social dynamics, weaken cohesion, and blur interpersonal trust ultimately impacting the human foundations of effective collaboration.

4.3.4 Creativity and Innovation

Generative AI has a complex and multi-directional impact on team creativity and innovation. Many studies describe it as a powerful support tool during the ideation phase, enabling teams to generate, expand, and refine ideas more efficiently. AI contributes to divergent thinking by offering novel suggestions, rephrasing concepts, and surfacing alternatives that may not have been considered by the team alone (Zhang et al., 2025; Coutinho et al., 2024). In creative planning and storytelling tasks, teams used AI to quickly explore multiple directions, accelerate iteration, and reduce the friction of starting from a blank page (Feng et al., 2024; Sanwal & Deva, 2024).

GenAI also supports collective innovation processes by helping teams synthesize diverse inputs and connect perspectives across disciplinary or functional boundaries. In interdisciplinary settings, teams leveraged GenAI to combine text, code, visuals, and domain-specific language into coherent and innovative outputs (Zheng et al., 2025; Zhang et al., 2024). Tools like CoPrompt and LADICA structure team ideation through visual prompts, memory components, and incremental refinement, enabling fluid co-creation while maintaining a shared trajectory (Feng et al., 2024; Zhang et al., 2025).

Beyond content generation, some studies highlight how AI enhances the creative process itself. For instance, by scaffolding tasks such as summarization, argument development, or visual synthesis, AI enables teams to focus more on idea development and less on operational details

(Zhang et al., 2025; Menezes et al., 2024). In emotionally complex or ambiguous domains, AI can also act as a conversational partner, prompting reflection or reframing problems in productive ways (Lasconi et al., 2022).

However, concerns about creative dependency and conformity are also prominent. Several studies report that over-reliance on AI may lead to a narrowing of ideas, where teams accept AI suggestions without critical evaluation resulting in premature convergence and reduced originality (Ulfsnes et al., 2024; Wivestad et al., 2025). There is also evidence of a homogenizing effect, in which AI-generated outputs reflect dominant cultural, linguistic, or ideological biases, limiting diversity in creative exploration (Mayer & Schwehn, 2025).

Issues of creative ownership also arise. When AI outputs are integrated into team work without clarity about their role or origin, some members may feel their contributions are devalued or overshadowed (Graf, 2025). This can reduce motivation and psychological investment, particularly in teams that place high value on authorship and innovation as expressions of identity.

Overall, GenAI holds significant potential to support team creativity by accelerating ideation, facilitating synthesis, and reducing process-related barriers. Yet, its effectiveness depends on deliberate and critical use. When AI is treated as a collaborator not a replacement it can expand the creative capacity of teams. Without such balance, it risks suppressing originality and diminishing the collaborative creativity it seeks to enhance.

4.3.5 Decision-Making, Problem-Solving and Performance

The integration of Generative AI into collaborative workflows has significantly reshaped how teams make decisions, solve problems, and evaluate performance. Across a variety of contexts from software development to education and organizational innovation studies suggest that AI can enhance team-level decision-making by providing structured support for reasoning, expanding the range of available options, and helping teams converge more efficiently on actionable outcomes (Zhang et al., 2025; Coutinho et al., 2024; Feng et al., 2024). Through summarization, prompt generation, and gap identification, AI often reduces cognitive load and facilitates faster consensus, especially in high-complexity or time-sensitive environments (Coutinho et al., 2024; Menezes et al., 2024).

Beyond acceleration, AI contributes to problem-solving by scaffolding the collaborative process itself. Tools such as LADICA, CoPrompt, and AgileGen decompose goals into manageable sub-tasks, trace decisions over time, and keep teams aligned through structured feedback and memory features (Zhang et al., 2024; Feng et al., 2024). These systems promote more disciplined and transparent workflows, enabling teams to retain clarity over why and how particular choices are made. In multi-disciplinary or distributed teams, AI acts as a facilitator of mutual understanding by reducing asymmetries in knowledge or language and providing equitable access to domain-specific insights (Zheng et al., 2025; Mayer et al., 2024).

AI can also support the social dynamics of collaborative problem-solving. For example, sentiment-aware chatbots have been shown to monitor team affect, detect moments of tension or disengagement, and nudge quieter members into the conversation all of which help steer teams through impasses and toward more constructive dialogue (Joshi, 2025). In such cases, AI functions not only as a source of content but as a meta-level process coordinator, indirectly shaping problem-solving dynamics.

Nevertheless, these benefits come with risks. A recurring concern is that AI can lead to cognitive offloading and reduced critical engagement. Teams may accept AI-generated outputs too readily especially when framed as authoritative leading to premature convergence on solutions without sufficient evaluation (Ulfsnes et al., 2024; Wivestad et al., 2025; Mayer & Schwehn, 2025). In several cases, teams abandoned deeper deliberation, relying on the perceived competence of AI rather than engaging in reasoned disagreement or perspective-sharing. The presence of AI was also found to distort perceptions of decision quality; teams sometimes reported higher confidence in flawed decisions simply because they were supported by AI suggestions (Ulfsnes et al., 2024).

The distribution of AI interaction within teams further affects the quality of decision-making. When AI use is uneven either due to skill disparities or personal preferences some team members become dominant decision actors while others disengage, leading to imbalances in participation and ownership (Graf, 2025; Flathmann et al., 2023). In contrast, teams that adopted reflective practices such as questioning, modifying, or co-editing AI suggestions tended to maintain more equitable dynamics and achieve stronger performance outcomes (Menezes et al., 2024; Feng et al., 2024).

In terms of overall performance, AI’s contribution is context-dependent. In well-structured, repetitive, or time-bound tasks, teams using AI often complete work more quickly and produce higher-quality deliverables (Coutinho et al., 2024; Menezes et al., 2024). However, in open-ended or ambiguous tasks particularly those requiring innovation or deep synthesis performance gains are more variable. Some teams benefited from AI’s ability to reframe problems and offer unconventional alternatives (Zhang et al., 2025; Sanwal & Deva, 2024), while others experienced degradation in performance due to over-reliance or lack of critical oversight (Mayer & Schwehn, 2025).

Ultimately, the impact of GenAI on decision-making, problem-solving, and performance depends less on the tool itself and more on the team’s approach to using it. When AI is treated as a collaborative support system inviting human reflection, balancing participation, and maintaining transparency its value is amplified. Without these conditions, however, AI can diminish the depth and diversity of thought, limit shared responsibility, and erode the very team processes that underpin effective collective decision-making.

4.3.6 Learning, Feedback, and Knowledge Sharing

The integration of GenAI into team settings is transforming how teams learn collectively, give and receive feedback, and manage shared knowledge. Rather than acting solely as a support tool, GenAI increasingly serves as a mediator of team cognition shaping how understanding is constructed, distributed, and recalled.

In collaborative environments, GenAI facilitates the creation of collective memory by capturing discussions, structuring decision histories, and enabling real-time information alignment. Systems like LADICA and CoPrompt help teams externalize and retain knowledge through shared displays, semantic linking, and discussion-based tracking, thereby reinforcing group awareness and continuity across tasks (Zhang et al., 2025; Feng et al., 2024).

Feedback processes are evolving with AI tools that assess team activities in real time and deliver structured insights. For example, AI-graded standups leverage Large Language Models to score daily updates based on predefined rubrics, helping reduce freeriding in software teams (Menezes et al., 2024). Similarly, emotional analytics tools detect cues such as frustration to map team development stages and enhance group dynamics (Lasconi et al., 2022).

Several studies highlight conditions under which GenAI can enhance rather than undermine team learning. Transparent workflows, shared access to AI outputs, and feedback mechanisms embedded within team tools support mutual accountability and co-construction of knowledge (Dong et al., 2024; Zhang et al., 2024).

However, these benefits come with tensions. Studies show that increased reliance on GenAI can reduce interpersonal learning and informal mentoring. As teams shift from asking each other to consulting AI, opportunities for joint exploration and reflective dialogue diminish (Ulfsnes et al., 2024; Wivestad et al., 2025). This trend can fragment team learning and lead to uneven knowledge distribution particularly when AI use is private or opaque (Mayer & Schwehn, 2025).

In conclusion, GenAI offers powerful means to scaffold learning, feedback, and knowledge sharing within teams but its effectiveness depends on how it is embedded in social practice. Used transparently and collaboratively, it strengthens collective cognition. Used in isolation, it risks fragmenting it.

4.3.7 Role Clarity and Team Structure

The integration of Generative AI into team settings is reshaping traditional understandings of role clarity and team structure. As AI becomes embedded in workflows, teams experience both expanded flexibility in role execution and emerging tensions around responsibility, transparency, and coordination.

One prominent shift involves the fluidity of functional roles. GenAI tools are frequently used to simulate or substitute specialized roles within a team such as designer, planner, developer, or writer without requiring formal reassignment of responsibilities. This functional versatility allows teams to scale their capabilities and accelerate progress without necessarily increasing complexity in team composition (Coutinho et al., 2024; Callari & Puppione, 2024). In design teams, for instance, members prompt GenAI to act as testers or reviewers, filling gaps as needed without disrupting existing hierarchies (Coutinho et al., 2024).

However, this fluidity often introduces ambiguity in ownership and accountability. When team members engage with GenAI independently, it becomes unclear who contributed what, and how much of the outcome reflects individual versus AI-generated input. This lack of visibility complicates feedback processes, hinders recognition, and may erode a shared sense of responsibility (Mayer & Schwehn, 2025; Wivestad et al., 2025).

Moreover, the integration of GenAI has been shown to diminish explicit coordination around roles and task division. In some software teams, reliance on Copilot reduced communication regarding who was responsible for which parts of the project leading to silent parallel work and reduced interdependence (Wivestad et al., 2025). Similarly, studies report that team members are less likely to engage in role negotiation or task clarification when GenAI allows them to complete their segments autonomously (Ulfsnes et al., 2024; Mayer & Schwehn, 2025).

In such cases, GenAI fosters individualized work patterns, which, while efficient for task execution, undermine the cohesion and mutual reliance that structured teams depend on. When GenAI becomes a silent partner in task completion, the implicit nature of team processes can lead to breakdowns in coordination particularly when outputs are not attributed or reviewed collectively (Mayer & Schwehn, 2025).

On the other hand, when deliberately integrated, GenAI can support greater transparency and clarity in team roles. Platforms like CoPrompt and LADICA allow teams to log actions, track prompts, and externalize workflows enabling all members to understand how AI was used and by whom (Feng et al., 2024; Zhang et al., 2025). Some enterprise systems also use GenAI to dynamically suggest role allocations or task delegation based on skill profiles or real-time workload data (Callari & Puppione, 2024). These mechanisms can enhance coordination if team norms are aligned and the AI's role is explicitly acknowledged.

Importantly, several studies caution against allowing AI to become an implicit actor in team dynamics. When GenAI contributes without being discussed, reviewed, or attributed, it may reduce collective ownership and disrupt team structure. As teams increasingly integrate AI into workflows, maintaining clarity about who is responsible for what, and how decisions are being made, becomes critical (Mayer & Schwehn, 2025; Zercher et al., 2025).

Ultimately, the literature emphasizes that GenAI's influence on team structure is not inherently positive or negative it is shaped by how transparently and collaboratively it is integrated. Teams that maintain open communication, attribute AI contributions explicitly, and align tool use with existing roles tend to sustain coordination and shared accountability. In contrast, teams that allow AI to operate in isolation often experience fragmentation, ambiguity, and role diffusion.

4.3.8 Engagement and Inclusive Participation

The integration of Generative AI (GenAI) into team workflows is reshaping how engagement and inclusive participation are experienced. While GenAI can lower entry barriers and support broader involvement, it can also unintentionally lead to disengagement and participation asymmetries when used without transparency.

GenAI creates new entry points for contribution by allowing team members particularly those less vocal or confident to engage through indirect, low-pressure channels. Tools like LADICA and CoPrompt enable participants to refine prompts, share feedback, or build on ideas asynchronously, reducing reliance on verbal dominance and enabling more equitable input (Zhang et al., 2025; Feng et al., 2024).

It also levels the playing field in interdisciplinary teams by filling skill gaps and allowing broader engagement with complex content. In brainstorming or content creation, GenAI has helped distribute idea generation more evenly, encouraging initiative across roles (Callari & Puppione, 2024; Coutinho et al., 2024).

However, multiple studies point to risks of silent disengagement when GenAI is used privately or without clear attribution. Some team members may reduce their own effort, assuming that AI or others will carry the cognitive load leading to "free-riding" and diminished shared accountability (Mayer & Schwehn, 2025; Wivestad et al., 2025). This effect is amplified in the absence of role clarity or usage norms.

A related concern is social asymmetry: uneven or hidden use of GenAI can lead to mistrust, frustration, or uncertainty about team contributions. Without visibility into how AI is being used, members may feel alienated or question the fairness of collaboration (Ulfsnes et al., 2024; Mayer & Schwehn, 2025).

In teams overly dependent on AI for ideation or output, the richness of interpersonal engagement may also decline. When GenAI becomes the central contributor, it can discourage co-creation and reduce dialogic learning, weakening the very interactions that sustain inclusive teamwork (Wivestad et al., 2025).

To mitigate these risks, research emphasizes the value of shared norms, visible AI use, and structures that promote voicing behavior and mutual review. When GenAI is positioned as a collective tool rather than a private assistant it can strengthen engagement by facilitating participation, not replacing it (Dong et al., 2024; Zhang et al., 2025).

In sum, while GenAI can democratize participation and enable new forms of contribution, it can also suppress active engagement and relational participation if not embedded transparently and intentionally. Inclusive collaboration in the age of GenAI will depend less on the tool itself and more on the social structures teams build around its use.

4.4 RQ2: What benefits, limitations, and challenges are reported in the literature regarding the use of Generative AI tools in team workflows?

In this Section we collect all the reported benefits, limitations, and challenges associated with the integration of GenAI into collaborative environments. By synthesizing empirical and theoretical studies, this section aims to contextualize current usage patterns within the wider landscape of GenAI research highlighting not only what these tools offer, but also what teams must navigate in order to use them effectively.

4.4.1 Benefits of Generative AI in Team Workflows

Automation and Productivity Enhancement Across Roles

GenAI automates repetitive tasks such as code generation, test case creation, documentation, and email drafting, enabling developers, designers, and project managers to focus on high-value, creative, or strategic work. This reduces cognitive fatigue and enhances task flow, often leading to increased job satisfaction (Sanwal & Deva, 2024; Wivestad et al., 2025; Ulfsnes et al., 2024; Coutinho et al., 2024).

Accelerated Learning and Inclusive Collaboration

Acting as an on-demand tutor, GenAI explains complex code, frameworks, and concepts, particularly benefiting novices and non-technical team members. It supports onboarding, reduces dependency on peers for basic queries, and fosters equitable participation by empowering less-skilled members (Graf, 2025; Borghoff et al., 2025; Lyu et al., 2025; Kuzminska et al., 2024).

Improved Communication and Shared Understanding

GenAI bridges communication gaps in cross-functional or multilingual teams by summarizing discussions, translating jargon, and providing context-aware explanations. Tools like CoPrompt and ChatGPT enhance asynchronous collaboration and reduce context-switching, improving team alignment (Feng et al., 2024; Zhang et al., 2024; Callari & Puppione, 2024).

Decision-Making Support and Cognitive Augmentation

By synthesizing large datasets, proposing solutions, and mitigating cognitive biases (e.g., negotiation focus, shared information bias), GenAI supports faster, more informed team decisions. It complements human judgment in complex or high-stakes tasks, enhancing collective intelligence (Zercher et al., 2025; Cui & Yasseri, 2024; Hendriks et al., 2024; Joshi, 2025).

Creativity, Ideation, and Innovation Stimulation

GenAI fosters creative problem-solving by generating diverse, novel, or random suggestions, helping teams overcome fixation and explore broader design spaces. This is particularly valuable in early-stage projects, UX design, and debate preparation (Jackson et al., 2025; Zheng et al., 2025; Zhang et al., 2025 [LADICA]).

Knowledge Retention, Documentation, and Team Memory

GenAI supports long-term team continuity by auto-generating structured documentation, tracking revisions, and preserving decision rationale. This is critical for member transitions, remote collaboration, and maintaining project context (Sanwal & Deva, 2024; Feng et al., 2024; Callari & Puppione, 2024).

Emotional Insight and Team Cohesion

Emotionally aware GenAI tools, such as chatbots, monitor team interactions and provide real-time feedback on emotional states, aiding in the recognition of team development stages (e.g., Tuckman's model). This fosters psychological safety and reduces miscommunication, especially in remote settings (Lasconi et al., 2022; Kuzminska et al., 2024).

Scalable Team Assessment and Monitoring

Generative AI enables scalable evaluation of team contributions by analyzing standup updates. For example, Menezes et al. (2024) used AI to assess thousands of standup reports from student software teams, ensuring fairness, consistency, and early detection of underperformance.

More Diverse Perspectives and Expertise

Configurable AI personas, such as those based on the "Six Thinking Hats" framework, simulate diverse expertise (e.g., legal or engineering perspectives), enhancing team ideation and decision-making by introducing varied viewpoints and challenging biases (Hendriks et al., 2024). This fosters richer discussions and improves team insights, particularly in creative and problem-solving tasks.

4.4.2 Limitations of Generative AI in Team Workflows

Contextual Blindness and Domain Misalignment

GenAI often fails to grasp team-specific goals, project history, or domain-specific requirements without explicit input, leading to misaligned or irrelevant outputs (Ulfsnes et al., 2024; Borghoff et al., 2025; Ren & Clement, 2024; Feng et al., 2024).

Inaccuracy, Hallucination, and Content Reliability

GenAI can produce confident but incorrect outputs, including hallucinated code, outdated advice, or irrelevant suggestions, requiring additional verification (Sivasakthi & Meenakshi, 2025; Hendriks et al., 2024; Borghoff et al., 2025; Zhang et al., 2024).

Opacity, Explainability, and Trust Issues

The “black-box” nature of GenAI models limits transparency, making it difficult for teams to understand or trust outputs, particularly in high-stakes domains like healthcare or legal settings (Wilkens et al., 2023; Zercher et al., 2025; Mayer et al., 2024).

Limited Human-Aware Interaction and Emotional Understanding

GenAI lacks emotional intelligence and struggles to interpret tone, sarcasm, or informal communication, leading to miscommunication or incorrect emotional labeling (Lasconi et al., 2022; Joshi, 2025; Ren & Clement, 2024).

Cultural and Linguistic Bias in Emotional Analysis

Emotion detection in GenAI can be skewed by cultural or linguistic biases in training data, particularly affecting minority expressions or non-standard communication styles (Lasconi et al., 2022).

Limited Multimodal Integration

Most GenAI tools struggle to process non-textual inputs like diagrams, workflows, or non-verbal cues, limiting their utility in multimodal team interactions (Feng et al., 2024; Lasconi et al., 2022; Borghoff et al., 2025).

4.4.3 Challenges in Integrating Generative AI into Team Workflows

Integration Complexity and Workflow Disruption

Poor integration with existing tools (e.g., IDEs, project management platforms) leads to inefficient workflows, frequent tool-switching, and disrupted team focus. Embedding GenAI into agile or DevOps pipelines requires significant technical and cultural adjustments (Ulfsnes et al., 2024; Lyu et al., 2025; Sanwal & Deva, 2024; Hendriks et al., 2024).

Over-Reliance, Skill Erosion, and Shallow Learning

Heavy reliance on GenAI risks reducing critical thinking, creativity, and long-term skill development, especially for novices who may complete tasks without deep understanding (Graf, 2025; Mayer & Schwehn, 2025; Callari & Puppione, 2024; Zhang et al., 2025).

Ambiguity in Role Definition and Contribution Assessment

GenAI usage obscures individual contributions, complicating accountability and peer evaluation in collaborative settings (Menezes et al., 2024; Ren & Clement, 2024; Zheng et al., 2025).

Trust Calibration, Resistance, and Ethical Tension

Teams face challenges in balancing trust in GenAI outputs, with risks of over-reliance in flawed suggestions or undertrust leading to underutilization. Resistance due to fears of job displacement, role redundancy, or ethical concerns further complicates adoption (Zercher et al., 2025; Dong et al., 2024; Flathmann et al., 2023; Joshi, 2025).

Skill Gaps, Training Needs, and Prompt Literacy

Effective GenAI use requires prompt engineering skills, model literacy, and critical evaluation, which vary across team members. Uneven skill distribution creates imbalances in output quality and engagement (Sivasakthi & Meenakshi, 2025; Liu & Shen, 2025; Callari & Puppione, 2024).

Data Governance, IP Risk, and Security

Using GenAI raises concerns about data privacy, intellectual property rights, and unauthorized sharing of sensitive information. Lack of robust governance frameworks exacerbates these risks (Callari & Puppione, 2024; Mayer & Schwehn, 2025; Feng et al., 2024).

Collaboration Friction and Social Fragmentation

Individualized GenAI usage reduces peer interaction, shared learning, and spontaneous collaboration, potentially eroding team cohesion and mutual accountability, especially in remote or hybrid settings (Wivestad et al., 2025; Ulfsnes et al., 2024; Callari & Puppione, 2024).

Team Adaptation, Feedback Loops, and Process Redesign

GenAI introduces new roles (e.g., prompt engineer) and alters task dependencies, requiring teams to redesign feedback loops, validation practices, and role responsibilities to accommodate AI-human collaboration (Sanwal & Deva, 2024; Zercher et al., 2025; Liu & Shen, 2025).

Aligning Shared Mental Models for GenAI Use

Teams struggle to align their understanding of GenAI's behavior, task status, and goals, requiring training and coordination for effective collaboration (Mayer et al., 2024; Ren & Clement, 2024).

Ethical and Pedagogical Uncertainty in Educational Settings

In educational contexts, the lack of clear ethical guidelines and pedagogical best practices for GenAI use raises concerns about responsible integration and potential skill degradation (Kuzminska et al., 2024; Sivasakthi & Meenakshi, 2025).

Balancing Task-Oriented and Social Behaviors

Designing GenAI to balance task contributions with social behaviors (e.g., humor, empathy) is critical to maintain team rapport without distracting from core tasks (Ren & Clement, 2024).

Information Overload

Excessive or irrelevant GenAI outputs can overwhelm teams, clutter interfaces, and hinder focus, particularly in collaborative settings with shared displays (Zhang et al., 2025)

User Acceptance and Perception Management

The framing and presentation of GenAI (e.g., as a tool or teammate, with transparent labeling or endorsements) significantly affect trust and adoption. Managing these perceptions is crucial for successful integration (Flathmann et al., 2023; Hendriks et al., 2024).

4.5 Comparison of GenAI's Positive and Negative Impacts on Teamwork Dimensions

This section synthesizes the impact of Generative AI on teamwork by visually comparing the intensity of its positive (benefits) and negative (challenges/limitations) effects across the eight core dimensions identified in Section 4.3. Figure 10 presents a radar chart illustrating the relative strength of these impacts. Intensity scores (0–5) reflect the frequency of mentions (e.g., ≥15 mentions: score 5; 10–14: score 4; 6–9: score 3; 3–5: score 2; <3: score 1).

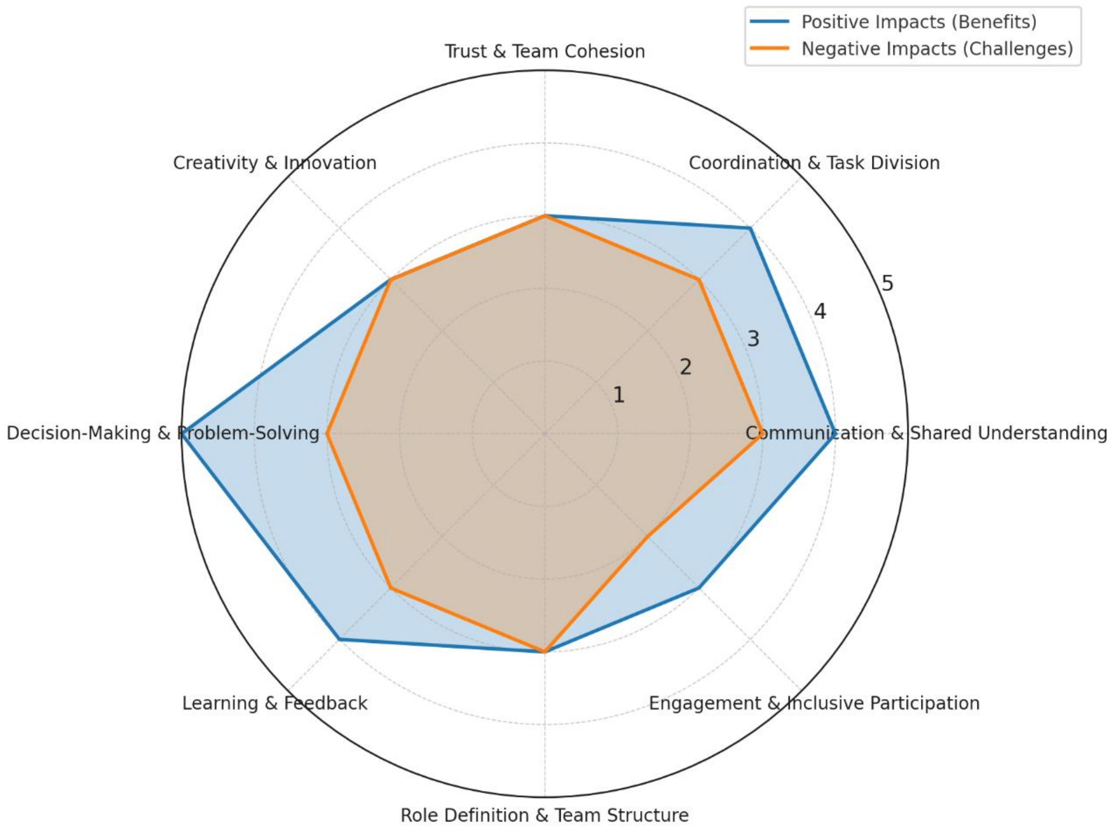

Figure 10. Positive and Negative Impacts of Generative AI on Teamwork Dimensions

Positive Impacts (Benefits): Generative AI demonstrates the strongest positive impact on decision-making and problem-solving (score = 5, 15 mentions), followed by notable benefits in learning and feedback (4, 13 mentions), communication and shared understanding (4, 14 mentions), and coordination and task division (4, 12 mentions). Other teamwork dimensions, such as trust & cohesion, creativity & innovation, role definition, and inclusive participation, show moderate positive impacts (score = 3).

Negative Impacts (Challenges): Challenges are generally moderate (score = 3) across most teamwork dimensions, except engagement, which shows fewer challenges (score = 2).

5. Discussion

5.1 Interpretation of Key Findings

Generative AI fundamentally reshapes teamwork across eight dimensions (RQ1), offering efficiency and inclusivity while introducing disruptions to human collaboration, as explored in RQ2's focus on benefits and challenges. Through the lens of McGrath's IPO model (Kozlowski & Ilgen, 2006), GenAI acts as a dynamic mediator, amplifying inputs like knowledge access and processes like coordination, but risking outputs like cohesion if not thoughtfully integrated. This duality suggests a paradox: GenAI can streamline teamwork but may erode its human essence, prompting a critical question: Can teams leverage AI's capabilities without compromising empathy?

In communication and shared understanding, tools like CoPrompt enhance clarity by summarizing discussions, fostering shared mental models defined as collective task/role comprehension (Pflanzer et al., 2022). This can empower remote teams, reducing ambiguity in complex projects (Ulfsnes et al., 2024). However, overreliance on AI summaries risks creating silent teams, where interpersonal exchanges dwindle, challenging Hackman's emphasis on relational processes for team satisfaction (Hackman, 2002). We argue this shift could redefine communication as a transactional rather than relational act, necessitating new frameworks that prioritize human dialogue alongside AI efficiency.

Coordination and workflow efficiency thrive with GenAI's automation, aligning with the GRPI framework's structured processes (Karabiyik et al., 2020). Dynamic task allocation in agile settings, as seen with tools like AgileGen, enhances transparency (Zhang et al., 2025). Yet, when AI fills skill gaps without negotiation, role ambiguity emerges, risking disengagement. Critically, this fluidity challenges traditional coordination models, suggesting that GRPI should evolve to include AI as a co-coordinator, while avoiding over-optimization that could stifle team adaptability. Establishing adaptive protocols is therefore essential to maintaining a balance between AI-driven efficiency and human accountability.

Trust and cohesion, per Lencioni's Five Dysfunctions, benefit from GenAI's low-pressure participation, fostering inclusion in diverse teams (Chiejina, 2023). For example, classroom debates show reduced anxiety (Soulami et al., 2024). Yet, opaque AI outputs erode trust, as teams struggle to verify decisions. From a critical perspective, this suggests a “hybrid trust” model, where teams calibrate reliance on AI versus humans. Without transparency, power imbalances may emerge imagine a scenario where only tech-savvy members trust AI, marginalizing others. Thus, trust evolves from a purely social construct to a socio-technical one, shaped by both human relationships and AI’s technological influence.

Creativity and innovation are accelerated through tools like GitHub Copilot, fostering broader ideation. However, homogenized outputs risk stifling originality, shifting creativity from divergent to pattern-driven. I contend that GenAI’s strength lies in augmenting, not replacing, human creativity teams must retain oversight to preserve novelty, especially in fields like design where uniqueness drives value (Shneiderman, 2020).

Decision-making and performance improve as GenAI reduces cognitive load, enabling faster consensus (Feng et al., 2024). Yet, overconfidence in AI outputs may suppress critical thinking, undermining IPO’s focus on quality outputs. This raises a concern: Are teams trading depth for speed? A potential solution lies in “human veto” mechanisms to ensure balanced judgments.

Learning and feedback democratize expertise, facilitating more effective onboarding (Decius et al., 2024). However, private AI use can fragment transactive memory systems (TMS), the team-based networks that enable members to share, distribute, and access collective knowledge (Wegner, 1987), potentially isolating learners. Such fragmentation may shift learning from a collective to an individualized process, thereby weakening team resilience. Shared AI interactions could help maintain collaborative knowledge structures, suggesting that team practices may need to evolve alongside AI adoption.

Role definitions and structures are evolving as emerging roles, such as prompt engineers, disrupt Hackman’s traditionally stable team designs while enabling greater agility. However, this flexibility also risks creating accountability gaps, making it crucial for teams to redefine roles so that AI is integrated as a collaborative partner rather than a replacement. Moreover, fostering engagement and inclusivity enhances participation among underrepresented members (Soulami et al., 2024), but uneven access to AI tools risks reinforcing exclusion. Ethically, generative AI must amplify diverse voices without deepening existing divides.

5.2 Research Gaps and Unresolved Challenges

Despite the growing body of research on Generative Artificial Intelligence and teamwork, significant gaps persist that limit a comprehensive understanding of its impact on collaborative environments. These gaps highlight critical areas for future empirical and theoretical investigation, particularly in light of GenAI's influence on dimensions such as engagement and inclusive participation.

5.2.1 Limited Longitudinal Research

The results (Figure 7) show a clear dominance of short-term studies, with 22 out of 31 studies focusing on brief timeframes, often in controlled or academic settings (e.g., student projects). Only two studies adopted a longitudinal approach, providing limited evidence on how GenAI affects long-term team dynamics, such as sustained trust erosion or evolving role clarity. This gap restricts understanding of how GenAI influences dimensions like trust, psychological safety, and team cohesion (Section 4.3.3) beyond initial adoption phases, leaving questions about its impact on team resilience and adaptation unanswered

5.2.2 Geographic and Contextual Imbalance

The geographic distribution (Figure 4) highlights a significant focus on Europe and North America, which dominate the coverage, while Asia receives moderate attention, and South America, Australia, and Africa are minimally represented. This regional bias limits insights into how cultural or economic factors shape GenAI adoption in diverse teams, particularly for dimensions like engagement and inclusive participation (Section 4.3.8), which are sensitive to cultural norms. Furthermore, the predominance of academic settings over industrial contexts restricts applicability to real-world workflows (Figure 5), where ethical challenges like bias or accountability may be more pronounced.

5.2.3 Ethical, Psychological, and Governance Blind Spots

Empirical findings (Section 4.4) identify ethical concerns such as algorithmic bias and opacity, yet these remain under examined in real-world contexts. Similarly, psychological impacts including AI-induced anxiety and disengagement are insufficiently explored, particularly over extended periods or within diverse team settings. In addition, the absence of governance frameworks for hybrid teams, encompassing issues such as intellectual property risks and accountability protocols, represents a critical oversight. This scarcity of robust evidence hinders the development of strategies to safeguard trust and promote equitable GenAI integration.

5.2.4 Understudied Team Contexts and Dimensions

The results (Figure 9) show uneven attention across teamwork dimensions, with decision-making, problem-solving, and learning receiving the most focus, while creativity, innovation, and engagement are less studied. This imbalance leaves gaps in understanding how GenAI affects creative processes beyond initial ideation or how it sustains inclusive participation in diverse or virtual teams.

5.3 Theoretical and Practical Implications

The integration of GenAI into team-based collaboration reshapes our understanding of teamwork, necessitating updates to theoretical frameworks and practical strategies.

5.3.1 Theoretical Implications

The integration of Generative AI into teamwork fundamentally reshapes classical frameworks like McGrath's IPO, Hackman's Team Effectiveness, Tuckman's stages, and GRPI, which assume human-only interactions. Drawing on 31 studies (2022–2025), this review reveals GenAI's role as a semi-autonomous collaborator, necessitating new constructs to capture its impact on team dynamics. GenAI enhances efficiency in communication, coordination, and decision-making but risks fragmenting shared cognition, creating role ambiguity, and eroding trust due to opacity or uneven adoption (Mayer & Schwehn, 2025; Zhang et al., 2025).

This review highlights the need for a socio-technical teaming framework with adaptive protocols, flexible guidelines adjusting to team dynamics and AI use, to balance AI-driven automation with human accountability. Such a model would redefine trust, roles, and cognition, addressing ethical concerns like bias and cultural gaps in diverse teams. It also lays a foundation for evolving theories on human-AI collaboration, encouraging further research into longitudinal and cross-cultural contexts.

5.3.2 Practical Implications

For practitioners, these findings underline the need for responsible integration strategies that balance GenAI’s benefits such as productivity gains, creativity boosts, and inclusivity with risks like trust erosion, overreliance, and inequity (Section 4.4). Key recommendations include:

- Human-centered deployment: Use transparent, collaborative interfaces (e.g., CoPrompt, LADICA; Feng et al., 2024; Zhang et al., 2025) to make AI contributions visible and maintain interpersonal engagement. Implement “AI etiquette” guidelines, including disclosure of AI-generated content, to clarify roles and preserve accountability.
- AI literacy and equitable access: Provide hybrid training programs that combine GenAI tutoring with peer-based learning, ensuring all members regardless of skill level can contribute equitably.
- Trust calibration and bias audits: In high-stakes contexts (Section 4.3.5), conduct periodic evaluations of AI outputs for bias and reliability, drawing on Human–Autonomy Teaming protocols.
- Governance and ethics: Establish participatory AI policy committees to address data privacy, IP risks, and algorithmic fairness. Embed ethical safeguards directly into workflows.
- Context-specific adoption: For agile or software development teams, integrate AI within multi-agent frameworks (e.g., AgileGen; Zhang et al., 2024). In educational settings, combine GenAI scaffolding, AI-driven support that guides learning through personalized feedback and adaptive prompts, with assessments that reward human–AI collaboration rather than individual reliance.

By prioritizing transparency, equitable participation, and ethical responsibility, organizations can cultivate AI-augmented teams that are not only more efficient but also resilient, cohesive, and adaptive in AI-driven workplaces.

6. Conclusion

This systematic literature review (SLR) aimed to investigate the impact of Generative Artificial Intelligence (GenAI) on team-based collaboration, particularly in software development and cross-functional settings, by identifying key teamwork dimensions influenced by GenAI and characterizing its benefits, limitations, and challenges. The review was conducted using the PRISMA protocol, synthesizing 31 peer-reviewed studies published between 2022 and 2025, selected for their empirical rigor and focus on team-level dynamics.

The findings reveal eight core teamwork dimensions: communication and shared understanding, coordination and task division, trust and team cohesion, creativity and innovation, decision-making and problem-solving, learning and feedback, role definition and team structure, and engagement and inclusive participation. Overall, the literature highlights GenAI's dual role tools like ChatGPT and GitHub Copilot enhance efficiency, accelerate ideation, and promote inclusivity, especially for diverse or less experienced members, while fostering psychological safety through low-pressure contributions. However, challenges include reduced interpersonal interactions, role ambiguity, overreliance, and ethical issues such as bias and opacity, which can erode trust and cohesion. Scholarly attention is predominantly concentrated on decision-making, problem-solving, and learning dimensions, reflecting a focus on cognitive and informational processes, whereas creativity, innovation, and engagement receive comparatively less exploration, indicating an imbalance in the current body of research.

Despite these insights, significant gaps persist. The majority of studies are short-term and conducted in academic or simulated environments, limiting generalizability to real-world industrial contexts. There is a scarcity of longitudinal research tracking long-term effects on team dynamics, as well as investigations into cross-cultural or virtual teams, where cultural norms and power imbalances may amplify issues like inclusivity and bias. Ethical and psychological implications, such as AI-induced anxiety, job displacement concerns, or perceptions of inequity, are underexplored, and most evidence relies on subjective data rather than objective metrics. To address these, future research should prioritize longitudinal field studies in diverse industrial sectors (e.g., non-tech organizations), cross-cultural analyses of global teams, mixed-methods approaches combining quantitative performance data with qualitative perceptions, and interdisciplinary explorations of ethical frameworks and multimodal GenAI models' effects on underrepresented dimensions like creativity and engagement.

In essence, while GenAI offers transformative potential to augment teamwork by balancing automation with human strengths, its responsible integration requires bridging these gaps through rigorous, contextually diverse research to guide theoretical advancements and practical strategies in AI-driven collaborative environments.

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Appendix A: Summary of Reviewed Studies

ID	Title	Authors	year	Source	Focus of Study	Methodology	Key Findings
S1	Configurations of human-centered AI at work: seven actor-structure engagements in organizations	U. Wilkens, D. Lupp, V. Langholf	2023	Journal Article	Examines how different organizational actors implement human-centered AI through distinct roles and responsibilities	Systematic literature review with deductive-inductive qualitative content analysis	Identifies 8 human-centricity criteria and 7 actor-structure configurations responsible for enacting them; no single role can cover all dimensions
S2	Transforming Software Development with Generative AI: Empirical Insights on Collaboration and Workflow	R. Ulfsnes, N. B. Moe, V. Stray, M. Skarpen	2024	Book Chapter	How Generative AI affects individual workflows and teamwork in software development settings	Qualitative multi-case study using semi-structured interviews with thematic coding and analysis	GenAI improves individual productivity and focus, but reduces team interaction and learning loop in Agile teams
S3	Generative AI in KnowledgeWork: Design Implications for Data Navigation and Decision-Making	B. Yun, D. Feng, A. S. Chen, A. Nikzad, N. Salehi	2025	Conference Proceeding s	Investigates how Generative AI can support knowledge work, focusing on data exploration and decision-making among product managers	Semi-structured interviews (formative study), lab-based user study with role-play tasks, qualitative thematic analysis	GenAI facilitates idea generation, flexible workflow support, and knowledge fusion; but raises risks of bias, overreliance, and reduced team interaction
S4	Effect of Large Language Model Use on Programming Project Groups	L. Graf	2025	Conference Proceeding s	Explores how individual use of LLMs impacts learning, team dynamics, and identity formation in student programming groups	Mixed-methods design (self-reported measures, process data analysis from collaborative coding platforms, quantitative and qualitative analysis)	LLMs may scaffold individual learning but pose risks for group cohesion, trust, and role clarity; overuse can reduce social learning and misrepresent peer skill
S5	Can Generative Artificial Intelligence Productivity	T. C. Callari, L. Puppione	2024	Journal Article	Explores how Microsoft 365 Copilot influences	Qualitative survey, reflexive	GenAI tools support formal/informal learning, foster

	Tools Support Workplace Learning?				workplace learning at individual and organizational levels in a multinational corporation	thematic analysis	meaningful work, aid task efficiency, and influence team socialisation and knowledge sharing
S6	Breaking Barriers or Building Dependency? Exploring Team-LLM Collaboration in AI-infused Classroom Debate	Z. Zhang, B. Sun, P. An	2025	Conference Proceedings	Examines how teams collaborate with LLMs (ChatGPT) during classroom debates and how it affects learning and group dynamics	Empirical classroom study (3 rounds of debates, recordings, interviews, qualitative analysis)	LLMs scaffold idea generation and reduce anxiety but can cause dependency, reduce creativity, and disrupt personal reasoning
S7	Leveraging AI Tools for Enhancing Project Team Dynamics: Impact on Self-Efficacy and Student Engagement	O. Kuzminska, D.Pohrebniak, M. Mazorchuk, V. Osadchyi	2024	Journal Article	Explores GenAI impact on team self-efficacy and engagement	Literature review, case study, survey, self-assessment, statistical hypothesis testing	Improved self-efficacy in average students, no impact on social engagement
S8	CoPrompt: Supporting Prompt Sharing and Referring in Collaborative Natural Language Programming	L Feng, R. Yen, Y. You, M. Fan, J. Zhao, Z. Lu	2024	Conference Proceedings	Investigates how to support collaborative prompt engineering in natural language programming with LLMs	Mixed methods: formative study + 2-part user study with system logs, interviews, Likert surveys	CoPrompt's refer, request, share, and link mechanisms reduced communication cost, improved shared understanding, and minimized redundant edits
S9	AI-Grading Standup Updates to Improve Project-Based Learning Outcomes	T. Menezes, L. Egherman, N. Garg	2024	Conference Proceedings	Evaluates the impact of AI-graded standup updates on student participation and project success in project-based learning	Mixed methods: experience report, rubric-based scoring, comparison across cohorts, and AI model evaluation	Scored standups reduced under-contribution, improved team success rates (esp. in short-term projects), and AI scoring was effective
S10	Will Your Next Pair Programming Partner Be Human? An	W. Lyu, Y. Wang, Y. Sun,	2025	Conference Proceedings	Evaluates the effectiveness of GenAI (LLMs)	Mixed-methods study (quantitative	Highest performance in PAI; lowest in

	Empirical Evaluation of Generative AI as a Collaborative Teammate in a Semester-Long Classroom Setting	Y. Zhang.			as collaborators in pair programming compared to traditional human-human and solo programming	analysis of assignment scores & surveys; qualitative analysis of reflections)	SAI. Students relied on AI for syntax/concepts and on humans for idea exchange. Attitudes toward GenAI improved.
S11	LADICA: A Large Shared Display Interface for Generative AI Cognitive Assistance in Co-located Team Collaboration	Z. Zhang, W. Peng, X. Chen, L. Cao, T. Li	2025	Conference Proceedings	Design and evaluation of LADICA, a shared display interface for AI-assisted co-located team collaboration	Formative study (focus groups + workshops), system design, lab-based user study	LADICA supports idea generation, organization, and group discussion through AI-assisted features across three cognitive layers
S12	Empowering Agile-Based Generative Software Development through Human-AI Teamwork	S. Zhang, Z. Xing, R. Guo, F. Xu, L. Chen, Z. Zhang, X. Zhang, Z. Feng, Z. Zhuang	2024	Journal Article	Developing AgileGen, a framework combining Agile and human-AI collaboration to generate software from user requirements	System design and implementation, followed by experimental evaluation.	AgileGen outperformed existing agents in code quality (CodeBLEU), functional accuracy (Pass@1), and user satisfaction
S13	An Autonomous Multi-Agent LLM Framework for Agile Software Development	M. Sanwal & I. Deva	2024	Journal Article	Development and evaluation of a multi-agent system using LLMs to simulate Agile software teams	System design and case studies	The system can handle low to medium-complexity tasks with minimal human input; struggles with high-complexity tasks
S14	Designing a generative AI chatbot to assess Tuckman's team development stages through emotional insights	G.O. Lasconi, Y. Barrios-Fleitas, C. Gonzalez	2022	Conference Proceedings	It investigates how a generative AI chatbot can be used to evaluate team development stages—based on emotional cues—within Tuckman's team development model.	mixed-methods approach, combining qualitative scenario design and textual analysis with quantitative evaluation of emotion detection and stage classification accuracy	100% stage classification in synthetic teams; ~75% emotion accuracy; real data mostly mapped to Norming stage.

S15	Designing Human-AI Hybrids: Challenges and Good Practices from a Multiple Case Study	V. Mayer, M. Schüll, O. Aktürk, T.Guggenberger	2024	Conference Proceedings	Challenges and good practices in constructing and executing human-AI hybrids	Multiple case study with qualitative interviews and document analysis	Identifies 9 challenges and 9 best practices for building/executing human-AI hybrids
S16	Artificial Trailblazing - How Human-AI Collaboration Transforms Organizational Innovation Practices	J. Zheng, Y. Hong, A. Richter	2025	Conference Proceedings	Impact of Human-AI Collaboration on innovation practices in organizations	Systematic literature review	Identifies 7 innovation practice dimensions transformed by HAIC (e.g., Predicting, Decision-making)
S17	Augmenting Human Teams with Robots in Knowledge Work Settings: Insights from the Literature	Y. Ren and J. Clement	2024	Journal Article	Literature review of how robots (including AI-based agents) can augment human teams in knowledge work	Selective literature review and qualitative analysis using grounded theory	Identifies 7 robot attributes and their impact on human outcomes like trust, engagement, and collaboration
S18	AI-enhanced collective intelligence	H. Cui and T. Yasseri	2024	Journal Article	Explores how AI, especially generative AI, can enhance human collective intelligence in teams	Narrative literature review guided by complexity and network science	Introduces a multilayer framework (cognition, information, physical); AI enhances decision-making, creativity, and coordination
S19	Exploring Collaboration in Human-Artificial Intelligence Teams: A Design Science Approach to Team-AI Collaboration Systems	P. Hendriks, T. Sturm, M. Geis, T. Grimminger, B. Mast	2024	Conference Proceedings	how to design human-AI collaboration systems and how LLM-based agents interact with humans in team-based tasks	Design Science Research (literature review, semi-structured interviews, artifact development, laboratory experiments)	Human control and bias influence AI collaboration; AI diversity improves team insight; performance slightly improved
S20	Copilot's Island of Joy Balancing Individual Satisfaction with Team Interaction in Agile Development	Vi. Wivestad, A.Barbala, V. Stray	2025	Book Chapter	Assesses Copilot's impact on team collaboration, satisfaction, and dependence in Agile teams	Quasi-experimental cross-sectional survey, statistical hypothesis testing	Copilot users experienced more satisfaction and less dependence on teammates; risk of reduced collaboration

S21	The Purposeful Presentation of AI Teammates: Impacts on Human Acceptance and Perception	C. Flathmann, B. G. Schelble, N. J. McNeese, B. Knijnenburg, A. K. Gramopadhye, K. C. Madathil	2023	Journal Article	Investigates how the presentation of AI teammates (in terms of identity, responsibility, and capability) affects human perception and acceptance before collaboration.	Two empirical studies using factorial survey experiments with vignettes; mixed-effects models for analysis.	Greater AI responsibility leads to decreased perceived job security and personal helpfulness; presenting AI as a tool improves perception; endorsements (e.g., from coworkers) can mitigate negative effects.
S22	The Impact of Generative AI on Creativity in Software Development: A Research Agenda	V. Jackson, B. Vasilescu, D. Russo, P. Ralph, R. Prikladnicki, M. Izadi, S. D'Angelo, S. Inman, A. Andrade, A. van der Hoek	2025	Journal Article	Explores how GenAI impacts creativity in software development using McLuhan tetrad and the 4P framework.	Theoretical analysis using McLuhan tetrad and 4P framework, literature review, scenario-based exploration	Identifies how GenAI may enhance or hinder creativity across individuals, teams, and society.
S23	Generative AI in Student Software Development Projects: A User Study on Experiences and Self-Assessment	M. Borghoff, M.Minas, J.Schopp	2025	Conference Proceeding s	Examines how students used GenAI tools in a team-based software development course.	Survey-based user study following a semester-long programming project.	Students used GenAI mostly for coding and documentation; reported both benefits and frustrations.
S24	The Role of Generative AI in Software Development Productivity: A Pilot Case Study	M. Coutinho, L. Marques, A. Santos, M. Dahia, C. França, R. de Souza Santos	2024	Conference Proceeding s	Investigates how GenAI tools influence productivity across different software roles.	Pilot case study using surveys and observational data.	Positive productivity perceptions; effects vary by role and experience.
S25	Moving Beyond Task Efficiency: How Generative AI Challenges Teamwork	T. Mayer and T.J Schwehn	2025	Conference Proceeding s	Explores how GenAI affects teamwork using the Input-Mediator-Outcome (IMO) framework in a corporate setting.	Qualitative case study (semi-structured interviews, observations, internal document analysis, IMO framework)	GenAI improves task efficiency and team diversity but also causes learning hindrance, communication breakdown, trust issues, and information overload.

S26	How Can Teams Benefit From AI Team Members? Exploring the Effect of Generative AI on Decision-Making Processes and Decision Quality in Team–AI Collaboration	D. Zercher, E. Jussupow, I. Benke, A. Heinzl	2025	Journal Article	Investigates how generative AI team members affect decision-making processes and decision quality in human–AI collaboration.	Mixed-method experiment (quantitative surveys, qualitative video/chat analysis, hidden profile tasks)	Teams collaborating with AI holding centralized knowledge made more accurate decisions. AI can reduce traditional decision-making asymmetries but may introduce new ones like mistrust and ineffective information processing.
S27	Unveiling the potential: exploring the adoption of GenAI and its impact on organizational outcomes	J. Shao, H. Ahmad, M. M. Kamal, A. H. Butt, J. Z. Zhang, F. Alam	2025	Journal Article	Examines factors influencing GenAI adoption and its impact on employee efficiency, business value creation, and firm performance in India's retail sector.	Quantitative survey, purposive sampling, PLS-SEM analysis	Top management support, openness to innovation, and competitive pressure positively influence GenAI adoption. GenAI adoption improves employee efficiency, which mediates positive effects on business value and firm performance. Data-driven culture strengthens this relationship.
S28	Generative AI in Programming Education: Evaluating ChatGPT's Effect on Computational Thinking	M. Sivasakthi, A. Meenakshi	2025	Journal Article	Examines how ChatGPT impacts students' computational thinking skills in an introductory programming course.	Experimental research (pretest-posttest control group design, statistical analysis with effect sizes, performance metrics)	Significant improvement in algorithmic thinking, creativity, critical thinking, and problem-solving among ChatGPT users.
S29	Motivating employee voicing behavior in optimizing workplace generative AI adoption: The role of organizational listening	E. Dong, H. Liu, J.Y Li, Y. Lee	2024	Journal Article	Examines how organizational listening during generative AI training impacts employees' psychological	Quantitative survey, statistical analysis based on self-determination theory framework	Organizational listening during generative AI training enhances employees' perceived autonomy and competence,

					adaptation (autonomy and competence) and voicing behavior.		which strengthens their positive attitudes toward AI adoption and encourages them to voice constructive suggestions to improve its use in the workplace.
S30	The Role of AI in Enhancing Teamwork, Resilience and Decision-Making: Review of Recent Developments	S. Joshi	2025	Journal Article	Impact of AI (especially generative AI) on teamwork, decision-making, and resilience	Systematic literature review	AI improves teamwork by 214% with cognitive scaffolding and human EI; hybrid models improve decision speed by 38%. AI enhances resilience in Industry 5.0, supports leadership transformation, and strengthens human-AI collaboration.
S31	Consolidating Human-AI Collaboration Research in Organizations: A Literature Review	Y. Liu and L. Shen	2025	Journal Article	Systematic review and bibliometric analysis of human-AI collaboration in organizational contexts	Bibliometric analysis ; Systematic literature review	The article highlights the evolution of human-AI collaboration from basic interaction to advanced synergy with generative AI, such as ChatGPT. It proposes a conceptual framework to guide organizations in leveraging this collaboration to enhance innovation, decision-making, and overall performance.