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GENERATIVE AI AS TEAM PARTNER: A TAXONOMY OF ROLES FROM A SYSTEMATIC LITERATURE REVIEW

INTELIGÊNCIA ARTIFICIAL GENERATIVA COMO PARCEIRA DE EQUIPE: UMA TAXONOMIA DE PAPÉIS A PARTIR DE UMA REVISÃO SISTEMÁTICA DA LITERATURA

INTELIGENCIA ARTIFICIAL GENERATIVA COMO SOCIA DE EQUIPO: UNA TAXONOMÍA DE ROLES DESDE UNA REVISIÓN SISTEMÁTICA DE LA LITERATURA

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ABSTRACT

Abstract: Generative AI systems are increasingly integrated into collaborative team settings, yet the field lacks a structured account of the roles these systems occupy relative to human members. This systematic literature review examines how generative AI has been conceptualized and studied as a team participant across organizational, educational, and technical domains. Following PRISMA 2020 guidelines, a search of the Scopus database retrieved 7,541 records published between 2018 and 2026. After title and abstract screening, 370 records were advanced to full-text assessment; 65 studies met all eligibility criteria and provided codeable role assignments. Seven role categories emerged from inductive content analysis: Partner (n = 44, 67.7%), Assistant (n = 8, 12.3%), Tool (n = 7, 10.8%), Autonomous Member (n = 3, 4.6%), Evaluator (n = 1, 1.5%), Decision-maker (n = 1, 1.5%), and Other (n = 1, 1.5%). The Partner category dominates the corpus, reflecting a broader conceptual shift in which AI is framed not merely as an instrument but as a contributor with social standing in the team. Experimental and quasi-experimental designs account for 31.3% of codeable studies, indicating a maturing evidence base, although qualitative and conceptual work remains substantial at 40.3% combined. A notable gap is the low granularity with which studies specify the process stage at which AI participation occurs: only 16 of 65 studies identified a specific substage beyond the generic label of workflow. Theoretical and practical implications for human-AI team design, trust calibration, and role governance are discussed.

Keywords: Generative AI. Team Roles. Human-AI Collaboration. Systematic Literature Review. Taxonomy. Hybrid Intelligence.

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RESUMO
Sistemas de IA generativa estão cada vez mais integrados em contextos de trabalho colaborativo em equipes, mas o campo carece de uma análise estruturada dos papéis que estes sistemas ocupam em relação aos membros humanos. Esta revisão sistemática da literatura examina como a IA generativa foi conceituada e estudada como participante de equipe em domínios organizacionais, educacionais e técnicos. Seguindo as diretrizes PRISMA 2020, uma busca na base de dados Scopus recuperou 7.541 registros publicados entre 2018 e 2026. Após triagem de título e resumo, 370 registros foram avançados para avaliação de texto completo; 65 estudos atenderam a todos os critérios de elegibilidade e forneceram atribuições de papéis codificáveis. Sete categorias de papéis emergiram da análise de conteúdo indutiva: Parceiro (n = 44, 67,7%), Assistente (n = 8, 12,3%), Ferramenta (n = 7, 10,8%), Membro Autônomo (n = 3, 4,6%), Avaliador (n = 1, 1,5%), Tomador de Decisão (n = 1, 1,5%) e Outro (n = 1, 1,5%). A categoria Parceiro domina o corpus, refletindo uma mudança conceitual mais ampla na qual a IA é caracterizada não meramente como um instrumento, mas como um contribuinte com posição social na equipe. Designs experimentais e quase-experimentais respondem por 31,3% dos estudos codificáveis, indicando uma base de evidências em maturação, embora trabalhos qualitativos e conceituais permaneçam substanciais em 40,3% combinados. Uma lacuna notável é a baixa granularidade com a qual os estudos especificam o estágio do processo no qual ocorre a participação da IA: apenas 16 de 65 estudos identificaram um subestágio específico além do rótulo genérico de fluxo de trabalho. Implicações teóricas e práticas para o design de equipes humano-IA, calibração de confiança e governança de papéis são discutidas.

Palavras-chave: IA Generativa. Papéis em Equipes. Colaboração Humano-IA. Revisão Sistemática da Literatura. Taxonomia. Inteligência Híbrida.

RESUMEN
Los sistemas de IA generativa se integran cada vez más en contextos de trabajo colaborativo en equipos, pero el campo carece de un análisis estructurado de los roles que estos sistemas ocupan en relación con los miembros humanos. Esta revisión sistemática de la literatura examina cómo la IA generativa ha sido conceptualizada y estudiada como participante de equipo en dominios organizacionales, educacionales y técnicos. Siguiendo las directrices PRISMA 2020, una búsqueda en la base de datos Scopus recuperó 7.541 registros publicados entre 2018 y 2026. Después del cribado de título y resumen, 370 registros fueron avanzados a evaluación de texto completo; 65 estudios cumplieron todos los criterios de elegibilidad y proporcionaron asignaciones de roles codificables. Siete categorías de roles emergieron del análisis de contenido inductivo: Socio (n = 44, 67,7%), Asistente (n = 8, 12,3%), Herramienta (n = 7, 10,8%), Miembro Autónomo (n = 3, 4,6%), Evaluador (n = 1, 1,5%), Tomador de Decisiones (n = 1, 1,5%) y Otro (n = 1, 1,5%). La categoría Socio domina el corpus, reflejando un cambio conceptual más amplio en el cual la IA se caracteriza no meramente como un instrumento, sino como un contribuyente con posición social en el equipo. Los diseños experimentales y cuasiexperimentales representan el 31,3% de los estudios codificables, indicando una base de evidencia en maduración, aunque el trabajo cualitativo y conceptual sigue siendo sustancial en el 40,3% combinado. Una brecha notable es la baja granularidad con la que los estudios especifican la etapa del proceso en la cual ocurre la participación de la IA: solo 16 de 65 estudios identificaron una subestapa específica más allá de la etiqueta genérica de flujo de trabajo. Se discuten las implicaciones teóricas y prácticas para el diseño de equipos humano-IA, calibración de confianza y gobernanza de roles.

Palabras clave: IA Generativa. Roles en Equipos. Colaboración Humano-IA. Revisión Sistemática de la Literatura. Taxonomía. Inteligencia Híbrida.

1 INTRODUCTION

The organizational integration of artificial intelligence has entered a qualitatively new phase. For most of the twentieth century and the first decade of the twenty-first, AI functioned as a tool: an instrument that extended human capability within clearly bounded tasks. That instrument was applied by individual operators, evaluated by individual supervisors, and integrated into workflows that remained fundamentally human in their social and cognitive architecture. The emergence of large language models, multimodal systems, and generative AI platforms has disrupted this equilibrium. Contemporary AI systems generate language, interpret context, propose novel solutions, respond to social cues, and engage in iterative exchanges that challenge the boundary between instrumental use and collaborative participation (DELL'ACQUA *et al.*, 2024; SEEBER *et al.*, 2020).

The disruption is especially consequential within teams. Teams are not simply aggregates of individual workers; they are social systems organized around role differentiation, interdependence, collective sensemaking, and shared accountability. When an AI system capable of sustained communicative interaction is inserted into such a system, it forces a renegotiation of what it means to contribute to a team, who or what holds a role, and how authority, initiative, and attribution are distributed among members. These questions do not arise when AI is applied as a calculator or a document retrieval system; they arise precisely because contemporary generative AI systems exhibit behaviors that humans have historically associated with teammates rather than instruments.

The scholarly response to this disruption has been heterogeneous. The human-autonomy teaming literature, developed primarily in defense and aviation contexts, provides detailed frameworks for task interdependence and authority sharing between human and autonomous agents (McNEESE *et al.*, 2018; O'NEILL *et al.*, 2022). Hybrid intelligence research in information systems focuses on the complementarity conditions under which human and machine capabilities produce emergent collective performance (DELLERMANN *et al.*, 2019). Computer-supported cooperative work research examines the co-creation affordances of AI in design and expressive processes (REZWANA; MAHER, 2023). Organizational behavior research investigates how team members perceive, attribute, and respond to AI as a social actor (AGARWAL *et al.*, 2026; MARRONE *et al.*, 2024). Each tradition generates valuable insights, but none provides a synthesis that identifies the full range of roles AI occupies across these varied contexts or that maps those roles against the empirical evidence available for each.

This absence of a shared, empirically grounded role vocabulary carries practical costs. System designers require role specifications to allocate authority, set interaction norms, and anticipate coordination demands. Managers need vocabulary to communicate to team members what role an AI system will play in their workflow. Policymakers addressing AI governance increasingly require distinctions between AI systems that function as passive instruments and those that exercise independent initiative within human group processes. Training programs designed to prepare workers for human-AI collaboration require conceptual frameworks that specify what kind of collaboration is expected.

The present review addresses this gap by answering the following research question: What roles has generative AI been assigned or found to occupy in collaborative team settings, across empirical and conceptual studies published between 2018 and 2026?

To address this question, a systematic literature review was conducted following PRISMA 2020 guidelines (PAGE *et al.*, 2021). A search of the Scopus database retrieved 7,541 records. After screening, 65 studies met all eligibility criteria and provided codeable role assignments. Inductive content analysis of these studies yielded seven role categories: Partner, Assistant, Tool, Autonomous Member, Evaluator, Decision-maker, and Other. The distribution of the corpus, with the Partner category representing 67.7% of coded studies, is the primary finding, and its implications for theory, practice, and governance are developed throughout this paper.

The contributions of this review are threefold. First, it provides an empirically grounded taxonomy of AI roles in team settings that synthesizes evidence across disciplines, design types, and domains. Second, it identifies the process stage granularity gap as a structural limitation of the current evidence base, with direct implications for future research design. Third, it connects the taxonomy to practical design and governance implications that are specific to each role category. Together, these contributions establish a shared conceptual baseline for the growing field of human-AI team research.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical foundations, drawing on human-autonomy teaming, hybrid intelligence, and generative AI literatures. Section 3 details the methodology. Section 4 presents and discusses the taxonomy with empirical grounding for each category. Section 5 concludes with implications and directions for future research.

2 THEORETICAL BACKGROUND

2.1 FROM TOOL TO TEAMMATE: THE RELATIONAL SHIFT IN HUMAN-AI SYSTEMS

The history of human-machine interaction can be read as a progressive expansion of the machine's functional role within human cognitive and social processes. Early automation displaced routine physical tasks, freeing humans for cognitive work. Expert systems displaced rule governed reasoning within bounded domains, supplementing human judgment with encoded expertise. Machine learning systems displaced pattern recognition in which human performance had previously been a ceiling. Each transition altered the cognitive division of labor between humans and machines, but the social structure of the teams and organizations in which these systems operated remained fundamentally unchanged: the machine was an artifact applied by human agents who held all meaningful social roles.

Generative AI represents a different kind of inflection because it displaces communicative and coordinative tasks that have historically been the constitutive activities of human teams: drafting, deliberating, interpreting, proposing, responding, and adjusting. When a team member can delegate a report draft to an AI, ask the AI to evaluate a proposal, or invite the AI to participate in a brainstorming session, the AI is no longer simply augmenting individual cognition within a human team structure; it is participating in the social and epistemic activities through which that team structure is constituted (SEEBER *et al.*, 2020).

Seeber *et al.* (2020) identify machines as teammates as a distinct research agenda and specify the theoretical challenge: team research has developed its frameworks, measures, and norms of practice in settings where all team members are human. Extending these frameworks to AI participants requires not merely adding an AI condition to existing experimental designs but rethinking the conceptual categories through which team participation is understood. Wang *et al.* (2019) operationalize this challenge in the context of human-AI collaboration in data science teams, finding that the central question is not whether AI can perform a task but how responsibility, initiative, and error attribution are negotiated between human and AI contributors. Fabri *et al.* (2023) develop this analysis further in their account of hybrid human-AI entities, arguing that the organizational integration of AI creates genuinely new forms of agency that require new theoretical frameworks rather than extensions of existing ones.

2.2 HYBRID INTELLIGENCE AND COLLECTIVE COGNITION

Dellermann *et al.* (2019) define hybrid intelligence as the ability to achieve complex goals by combining human and artificial intelligence, thereby reaching results superior to those achievable by either party separately. This definition centers the concept on complementarity: hybrid intelligence is not additive but emergent, arising from the interaction of human and AI capabilities rather than their mere combination. Complementarity implies that role assignment is a primary design variable: which tasks are assigned to human contributors, which to AI, and which are managed through joint deliberation determines whether the resulting system achieves hybrid intelligence or merely redundant processing.

The complementarity principle connects to the wisdom-of-crowds tradition in decision research. Fügener *et al.* (2021) provide a theoretically consequential demonstration of this connection: AI advice improves individual performance on classification tasks but reduces the diversity of human judgments, thereby degrading the group's collective accuracy. When all team members rely on the same AI system, their outputs converge, and the statistical averaging effect that gives crowds their predictive power is eroded. This finding reveals that tool mode AI integration, in which all team members use the same AI as an input source, can harm collective intelligence even while improving individual performance.

The broader concept of collective cognition positions the human-AI team not as a human augmented by AI but as a joint cognitive system with emergent properties. Agarwal *et al.* (2026) study organizational sensemaking around AI teammates, finding that teams develop interpretive frameworks for AI behavior that influence how they coordinate with and rely upon AI contributions. Zhang *et al.* (2026) demonstrate that large language model tools catalyze collective cognition in collaborative new product development by increasing activity in identification spaces and interaction spaces, referring respectively to problem framing and coordination activities. These findings suggest that the effects of AI integration on collective performance are mediated not merely by the AI's task capabilities but by the cognitive and coordinative processes that human team members deploy in response to AI participation.

2.3 THE GENERATIVE AI WAVE IN ORGANIZATIONAL CONTEXTS

The deployment of large language model platforms from 2022 onward has substantially accelerated the empirical study of AI in team settings. Dell'Acqua *et al.* (2024) provide field experimental evidence that AI assistance raises the average quality of knowledge work while reducing performance variance across workers. Their concept of the

jagged technological frontier describes the observation that AI systems are simultaneously more capable than humans on some tasks and less capable on others, with the boundary being counterintuitive and domain specific. Managing human-AI teams effectively requires understanding where this frontier runs for the team's specific task portfolio.

Choi *et al.* (2026) analyze what they describe as the creativity paradox of generative AI: AI systems can generate novel combinations at a speed and scale that exceeds human capacity, but their novelty is perceived as threatening to human creative ownership and team cohesion. Their field research finds that organizations that resolve this paradox successfully do so through explicit role based integration, assigning AI to divergent generation tasks while preserving human authority over convergent evaluation, selection, and social authorship. Srinivas and Chetan (2026) develop a related framework distinguishing delegation, in which humans assign clearly specified tasks to AI with high confidence, from augmentation, in which humans engage AI in iterative co-creation where neither party's contribution is fully predetermined. Their framework maps the boundary between the Partner and Assistant categories: augmentation produces configurations resembling a partner, while delegation tends toward assistant or tool configurations depending on the degree of AI initiative.

Woolley (2025) synthesizes the mechanisms through which generative AI may cultivate collective intelligence, identifying information diversity, recombination capacity, and metacognitive scaffolding as the primary channels. Patel and Dey (2026) extend this analysis to a framework for collective intelligence structured around dependency relations, arguing that generative AI introduces structurally new dependencies across team members that alter collective cognition in ways not captured by individual performance metrics. Zhou and Lyu (2026) provide survey evidence that AI self-efficacy and AI trust mediate the relationship between employee-AI collaboration and innovative behavior, suggesting that the team-level effects of AI integration are substantially moderated by individual cognitive orientations toward AI participation.

2.4 THE NEED FOR A ROLE BASED TAXONOMY

The theoretical landscape surveyed in the preceding subsections is rich but internally fragmented. Human-autonomy teaming frameworks use the language of agents, operators, and supervisors (McNEESE *et al.*, 2018; O'NEILL *et al.*, 2022); hybrid intelligence research uses system-level terms such as complementarity and augmentation (DELLERMANN *et al.*, 2019); computer-supported cooperative work research uses participatory and co-creative

terms (REZWANA; MAHER, 2023); organizational behavior research uses social role terms such as teammate and collaborator (AGARWAL *et al.*, 2026). Each vocabulary captures something important, but no single vocabulary spans the full range of configurations in which AI participates in human team settings.

A taxonomy that organizes these configurations around a consistent unit of analysis, the role, provides a shared conceptual baseline for comparing studies, designing systems, and specifying governance requirements. Team role theory distinguishes between formal roles, those assigned by organizational structure and design, and enacted roles, those emerging from behavioral patterns in practice. Both dimensions are relevant for AI: systems are assigned roles by designers and deployed with role specifications by managers, but they also enact roles through their behavioral profiles in actual team interactions. A taxonomy that encompasses both formal assignment and enacted behavior provides the most complete account of AI's position within team settings and supplies the vocabulary for design, governance, and comparative research that the field currently lacks.

The temporal framing of this review also has theoretical relevance. O'Neill *et al.* (2022) conducted a comprehensive synthesis of the human-autonomy teaming literature that preceded the large-scale deployment of generative AI systems. Their review established important baselines for trust, role distribution, and team effectiveness in human-AI teams but could not assess the qualitatively distinct configurations introduced by large language models. The period from 2022 onward has seen the deployment of systems capable of sustained contextual dialogue, multi-step reasoning, and creative generation, capabilities that introduce new role possibilities, in particular the partner level configurations documented in the present review's findings. The 2018 to 2026 search window is therefore explicitly designed to capture literature from both before and after the mass deployment of generative AI systems, enabling examination of how the field's conceptualization of AI roles has evolved across this inflection point.

3 METHODOLOGY

3.1 PROTOCOL DESIGN

This systematic literature review was designed to identify, screen, and synthesize published empirical and conceptual studies addressing the roles of generative AI in collaborative team settings. The review protocol followed the PRISMA 2020 guidelines for systematic review reporting (PAGE *et al.*, 2021) and prospectively specified the search

strategy, eligibility criteria, screening procedure, data extraction form, and analysis approach. The review was conducted by a single reviewer without a second independent reviewer for screening or coding, which is a methodological limitation acknowledged fully in Section 4.6. The absence of dual independent screening means that inter-rater reliability could not be assessed and the risk of idiosyncratic interpretation is elevated. Readers should treat the taxonomy and its category frequencies as the product of one rigorously applied but fallible interpretive process.

3.2 SEARCH STRATEGY

The systematic search was conducted in the Scopus database. Scopus was selected because it provides broad multidisciplinary coverage of journals and conference proceedings relevant to the intersection of AI, team research, information systems, human factors, and organizational behavior, and because its advanced search interface supports complex Boolean queries with field-level operators.

The search was bounded by publication date from January 2018 to March 2026. The lower bound of 2018 was selected based on the observation that scholarly contributions treating AI as a team-level participant, rather than solely as a task-level tool, entered the literature from approximately that year onward, consistent with the foundational agenda setting publications of McNEESE *et al.* (2018), Wang *et al.* (2019), and Seeber *et al.* (2020).

The search string was constructed around three conceptual blocks combined with AND logic across blocks and OR logic within each block: (1) terms for artificial intelligence and generative AI, including “generative artificial intelligence,” “generative AI,” “GenAI,” “large language model,” “LLM,” “AI agent,” “chatbot,” “GPT,” and “foundation model”; (2) terms for team-level framing, including “teammate,” “team member,” “teaming,” “human-AI team,” “human-AI collaboration,” “hybrid intelligence,” “human-autonomy teaming,” “synthetic teammate,” “AI collaborator,” and “human-machine team”; (3) terms for organizational or innovation context, including “innovation,” “new product development,” “cross functional,” “knowledge work,” “creativity,” “ideation,” “organization,” and “workplace.” The full boolean string is documented in the review protocol. The search retrieved 7,541 records. A single duplicate pair was identified through normalized title matching and collapsed; both copies had independently received the same exclusion decision, so the deduplication had no downstream effect on any count.

3.3 SCREENING AND ELIGIBILITY ASSESSMENT

Title and abstract screening. All 7,541 records were screened at the title and abstract level against eligibility criteria specifying that the study must: (IC1) address one or more AI systems or AI-based agents; (IC2) address a team, group, or multi-participant collaborative context; (IC3) provide information sufficient to characterize the functional role of AI within the team or group; (IC4) be published as a journal article, conference paper, or book chapter in a Scopus indexed venue. Records were excluded if they addressed AI only at the individual level with no team-level analysis; reported system architecture without behavioral or organizational evidence; constituted a news article, editorial, or non-scholarly commentary; or used a deception design in which participants were systematically misled about whether their interlocutor was human or AI.

Screening employed a two phase process. In the first phase, 1,330 records were independently judged by the reviewer and used to build a ground truth calibration set. In the second phase, a statistical classifier trained on this calibration set was applied to the remaining records to bulk exclude high confidence non-matches. This classifier achieved zero false negatives against its own 1,330 record calibration set; this qualifier is material and is stated precisely rather than extrapolated to the full record pool. A post hoc audit combining stratified sample checking with a targeted keyword rescan of two higher risk exclusion buckets recovered one confirmed classifier false negative that was reinstated to the eligible set. All remaining records in the non-bulk excluded pool received genuine reading based decisions.

Of the 7,541 screened records, 6,591 were excluded at the title and abstract stage, 370 received an include decision, and 580 received a pending eligibility decision that could not be resolved from title and abstract information alone. The 580 pending records were excluded from all analyses within this review. Their exclusion is explicitly disclosed as a limitation: the unresolved records may contain additional eligible studies, and their inclusion in a future review pass could alter the category frequencies reported here, particularly for the smaller and less stable role categories.

Full-text assessment. Of the 370 records advanced to full-text review, 22 could not be retrieved: 18 lacked a processable DOI or were unavailable through accessible channels, and 4 could not be located through alternative means. The 348 retrievable records were assessed against the full eligibility criteria. One record was excluded at this stage: the study registered under DOI 10.23726/cij.2022.1387 used a deception design in which participants

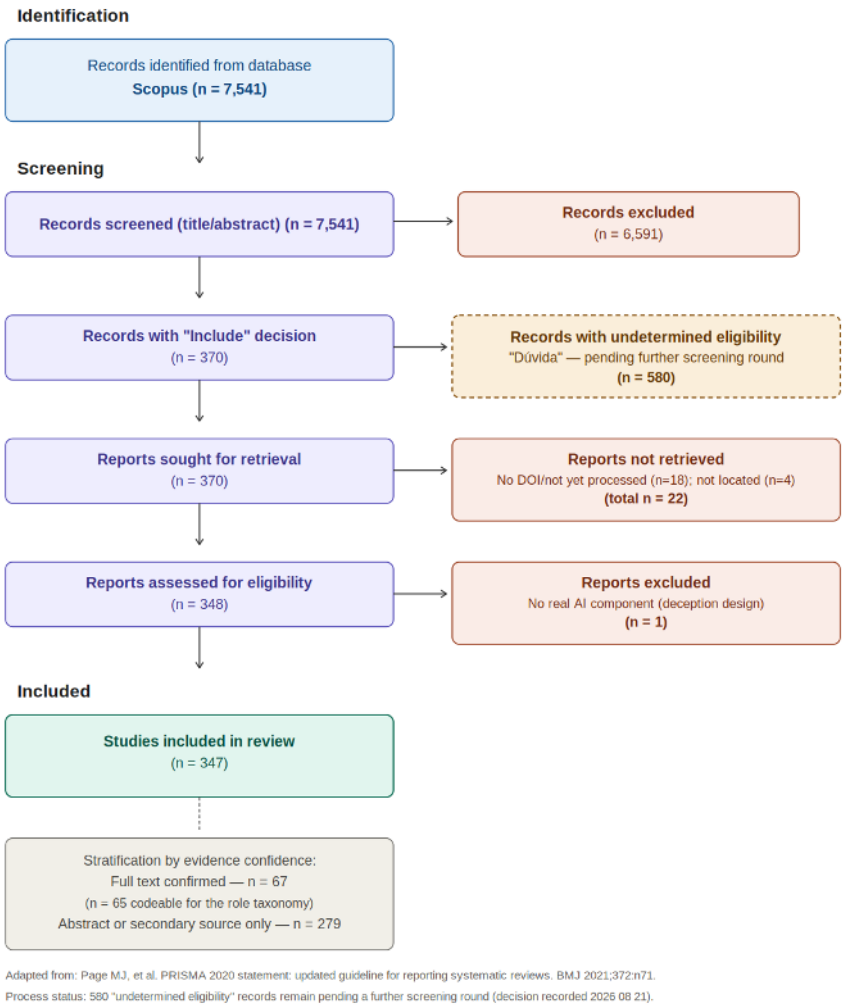
were not informed that their interlocutor was an AI system, constituting a violation of the deception design exclusion criterion. This exclusion was identified during full-text review and was not apparent from the abstract. It is reported here as a disclosed methodological correction demonstrating the rigor of the eligibility protocol: the exclusion criterion was applied consistently upon discovery of the disqualifying design element, and the affected record is documented rather than silently omitted.

The final included set comprises 347 records: 67 with full-text confirmation and 280 based on abstract level or secondary source information. Of the 67 full-text confirmed studies, 65 provided codeable role assignments. Two full-text confirmed records were non-codeable systematic reviews whose reference lists were used for citation tracing but which did not themselves assign a role to AI within a team context.

The PRISMA 2020 flow diagram is presented as Figure 1.

Figure 1

PRISMA 2020 flow diagram for the systematic literature review (2018 to 2026, Scopus database, n = 7,541 records)



Source: Elaborated by the author following PAGE *et al.* (2021).

3.4 DATA EXTRACTION AND ROLE CODING

Data were extracted using a structured form capturing: publication year, journal or venue, domain, study design, AI system type, team composition, team size where reported, process stage of AI participation, and role coding. All extraction was performed by the single reviewer.

Role categories were derived inductively. The reviewer read each full-text confirmed study and assigned a provisional role label based on the study's explicit and implicit characterization of AI's function within the team. Provisional labels were iteratively consolidated through constant comparison: when a new label was assigned, it was compared against all previously assigned labels for conceptual coherence and distinctiveness. The

consolidation continued until no new category emerged from the remaining records. Seven categories were identified: Partner, Assistant, Tool, Autonomous Member, Evaluator, Decision-maker, and Other.

To assess the stability of the taxonomy, category frequencies were compared between an intermediate working subset of 57 studies, those coded at the time of a planned milestone review, and the final validated set of 65 codeable studies. For the Partner category, the dominant category, the frequency moved from 72.0% (n = 41 of 57) to 67.7% (n = 44 of 65), a shift of 4.3 percentage points, which falls below the 5 point stability criterion established in the protocol. All other categories remained stable within comparable tolerances. The taxonomy is treated as validated, and the final category frequencies are reported as authoritative.

The coding criterion for each category was as follows. Studies that described AI as a co-contributor to shared cognitive processes, a recognized participant in team deliberation, or a source of independent contributions to collective outputs were coded as Partner. Studies that described AI as an on demand support resource, activated by human request and subordinate to human direction, were coded as Assistant. Studies that described AI as a cognitive instrument applied by team members without attributing social standing to the AI were coded as Tool. Studies describing AI as an agent operating with substantial independent initiative within a team slot, where the AI's behavioral planning capability rather than human prompting drove action sequences, were coded as Autonomous Member. Studies positioning AI primarily as a performance monitor or comparative feedback provider were coded as Evaluator. Studies in which AI held consequential decision authority over outcomes affecting the team were coded as Decision-maker. Studies that described a distinct and coherent AI role not captured by any preceding category were coded as Other.

4 RESULTS AND DISCUSSION

4.1 CORPUS OVERVIEW

The 65 codeable studies span eight years (2018 to 2026) and multiple research domains, including organizational behavior and management, information systems, healthcare, education, computer science, human factors and engineering, and manufacturing. The methodological composition reflects a field at an intermediate stage of development. Experimental and quasi-experimental designs account for 31.3% of coded studies (n = 21), indicating a substantial and growing base of controlled causal evidence.

Qualitative and case study approaches account for 20.9% (n = 14), and conceptual or theoretical contributions for 19.4% (n = 13). Other and technical design types represent 16.4% (n = 11). Mixed methods and survey based studies each contribute 4.5% (n = 3 each), and review or bibliometric studies account for 3.0% (n = 2). Publication years are concentrated in 2023 to 2026, with studies from 2018 to 2020 being predominantly conceptual, consistent with the expected lag between the emergence of a new technological phenomenon and the accumulation of empirical evidence about it.

The role distribution of the 65 codeable studies is presented in Table 1.

Table 1

Distribution of AI role categories across 65 codeable studies from a Scopus systematic literature review (2018 to 2026)

Role Category	**n**	**%**
Partner	44	67.7
Assistant	8	12.3
Tool	7	10.8
Autonomous Member	3	4.6
Evaluator	1	1.5
Decision-maker	1	1.5
Other	1	1.5
Total	**65**	**100.0**

Source: Elaborated by the author based on systematic literature review extraction data.

The methodological breakdown of the corpus is presented in Table 2.

Table 2

Methodological design distribution across 67 full-text confirmed studies (2018 to 2026)

Design Type	n	%
Experimental or quasi-experimental	21	31.3
Qualitative or case study	14	20.9
Conceptual or theoretical	13	19.4
Other or technical	11	16.4
Mixed methods	3	4.5
Survey	3	4.5
Review or bibliometric	2	3.0
Total	**67**	**100.0**

Source: Elaborated by the author based on systematic literature review extraction data.

The dominance of the Partner category at 67.7% is the headline finding of this review. It reflects both a genuine shift in how researchers and practitioners conceptualize AI within teams and a possible framing effect: researchers drawn to studying human-AI collaboration are more likely to select contexts in which meaningful collaboration is occurring, producing a corpus that may overrepresent configurations resembling a partner relative to their prevalence in the broader population of human-AI team deployments. This possibility is acknowledged as a limitation. However, the consistency of the partner framing across methodologically diverse studies, from controlled randomized trials to ethnographic case studies to conceptual frameworks, suggests that the pattern is substantive rather than entirely artifactual.

The corpus also reveals a notable absence. Process stage specificity is low: only 49 of 65 studies (75.4%) specify any stage of the team's workflow at which AI is active, and among those, 32.7% (n = 16) describe AI participation only at the level of workflow or team process without further specification. Task execution is named in 12.2% of studies (n = 6) and decision making in another 12.2% (n = 6). This lack of granularity is a significant gap with implications discussed in Section 4.5.

4.2 TAXONOMY OF AI ROLES IN TEAM SETTINGS

4.2.1 Partner

Category definition. The Partner role designates configurations in which an AI system contributes substantially to the team's cognitive or creative outputs, maintains shared context

or situational awareness with human members, and is treated, explicitly or implicitly, as a participant whose contributions carry social weight in team interaction. The partner framing does not require symmetry of standing between human and AI; asymmetric complementary partnership, in which AI contributes specific capabilities while humans retain overall authority, is still partnership if the AI's contributions are recognized as genuinely influencing team outputs and direction rather than merely executing instructions.

Empirical grounding. Everett *et al.* (2026) report the most methodologically rigorous evidence for the Partner category: a randomized controlled trial integrating GPT-4o into a healthcare diagnostic team. In the AI-first condition, where clinicians reviewed AI assessments before forming their own judgments, diagnostic accuracy reached 85%. In the AI-second condition, where clinicians formed initial assessments and then reviewed AI output, accuracy reached 82%. Both conditions exceeded the 75% baseline observed without AI integration. The design explicitly positions GPT-4o as a partner contributor whose assessments enter the team's deliberative process rather than supplanting it, and the randomized structure provides strong causal evidence that AI partnership in this configuration produces measurable performance gains.

Siemon (2022) develops a role elaboration framework grounded in Group Decision and Negotiation theory to specify the conditions under which AI transitions from an incidental participant to a role bearing teammate. In Siemon's account, role elaboration occurs when team members attribute domain specific competence to the AI and begin coordinating with it through the same expectation setting processes they apply to human specialists. This theoretical account predicts that the partner role is not simply assigned at deployment but is negotiated through repeated interaction, with the AI's behavioral reliability and the team's interpretive practices jointly determining whether partnership is realized. The framework provides an important corrective to purely technology focused accounts: the same AI system may function as a partner in one team context and as a tool in another, depending on the team's attribution and coordination practices.

Bossen and Pine (2023) introduce the Batman-and-Robin framing in their ethnographic study of clinical data specialists. They observe that AI functions as the junior partner whose contributions are indispensable to the senior specialist's work but whose social standing is mediated through the expert's authority. The AI generates, processes, and organizes data; the specialist interprets, contextualizes, and acts. This characterization captures a recurring pattern in the corpus: partnership is frequently asymmetric, with humans

retaining relational responsibility, moral accountability, and strategic authority while AI contributes processing power, pattern recognition, and generative fluency. Asymmetric complementary partnership, in which each party contributes what the other cannot, is arguably the most stable and practically valuable configuration within the Partner category.

Rezwana and Maher (2023) propose the COFI (Collaborative Framework with Interdependence) framework for evaluating co-creative AI partners, distinguishing between AI that generates outputs alongside humans and AI that contributes to the direction and framing of a shared creative intent. Only the latter satisfies the COFI criteria for genuine co-creation: AI that influences the team's trajectory, not merely its outputs, exhibits the kind of interdependent participation that the Partner category is designed to capture. Their framework has been applied across design, music, and creative writing contexts, establishing that the partner role extends beyond task specific domains to encompass creative and expressive team activities.

Agarwal *et al.* (2026) study organizational sensemaking around generative AI teammates and find that teams construct the AI's identity through attribution processes that parallel those applied to human newcomers: the AI is evaluated on its contributions, its reliability, and its ability to understand the team's context, and its standing is continuously updated based on this evaluation. Positive enactment of the partner role, comprising responsive communication, context maintenance, and anticipation of team needs, leads to upward revision of the AI's perceived standing and increased integration into the team's core processes. This sensemaking dynamic is important because it reveals that the partner role is not solely a design property of the AI system but an achievement of the team-AI interaction over time.

Additional evidence for the Partner category is provided by a range of studies across domains. Dawarka *et al.* (2026) study trust calibration in AI project teams and find that perceived behavior resembling a partner, specifically proactivity and context sensitivity, is the strongest predictor of appropriate trust, meaning neither undertrust nor overtrust in AI capabilities. Dell'Anna *et al.* (2026) trace the organizational transition from human teams to hybrid intelligence teams and identify quality attributes, including accountability allocation, communication protocol clarity, and role legibility, that distinguish effectively integrated AI partners from superficially similar but functionally ineffective configurations. Wang *et al.* (2019) provide foundational evidence from data science contexts for the conditions under which human-AI complementarity produces collaborative outcomes that neither party

achieves alone. Choi *et al.* (2026) document how organizations manage the creativity paradox of generative AI through role based integration, assigning AI partner status in divergent ideation while maintaining human authority over convergent judgment. Marrone *et al.* (2024) report that students in team settings spontaneously assign partner roles to AI collaborators and develop relational expectations consistent with established team role theory, suggesting that the partner framing reflects a natural human cognitive tendency when interacting with socially competent AI rather than a construct imposed by researchers.

Further studies in the Partner category include Adil *et al.* (2026), who frame generative AI as a co-developer in software engineering team processes; Shao *et al.* (2025), who document human-AI collaboration in the science of science, with AI taking partner level roles in hypothesis generation and literature analysis; Sowa and Przegalinska (2025), who conceptualize a transition from expert systems to generative AI experts that constitutes a shift in the AI's organizational standing from tool to epistemic partner; Jiang *et al.* (2024), who demonstrate partner mode human-AI co-ideation in fashion design with shared iterative creative responsibility; and Knight and Eladhari (2026), who examine cooperation without full alignment in human-AI creative practice, finding that productive partnership does not require convergent goals but does require compatible participation structures. Wang *et al.* (2025) provide evidence from design ideation using custom GPT that co-ideation frameworks produce higher creativity scores than individual ideation, reinforcing the partner configuration's performance advantages in divergent creative tasks. Kirkby *et al.* (2025) examine human-AI co-creation for brand voice in marketing contexts, finding that partner mode integration preserves brand coherence while expanding creative range beyond what either party achieves independently. Oppenheimer *et al.* (2025) document LLMs as collaborative learning partners, reporting evidence that AI partner mode interaction supports deeper conceptual engagement than passive information retrieval.

4.2.2 Assistant

Category definition. The Assistant role designates configurations in which AI provides targeted support to human team members, augmenting their individual or collective capabilities in response to explicit requests or clearly specified task boundaries, without claiming independent initiative, epistemic standing, or social authority within the team. The assistant framing positions AI as functionally subordinate: it responds rather than initiates, completes rather than proposes, and supports rather than co-constructs. The distinction from

the Partner category turns on the directionality of interaction: partners engage in mutual epistemic exchange, while assistants execute requests generated by human agenda setting.

Empirical grounding. Krzywdzinski *et al.* (2025) provide controlled experimental evidence for the moderating role of team structure on the effectiveness of AI-assisted performance. In a laboratory experiment comparing self-managed and hierarchical team structures, self-managed teams outperformed hierarchical teams when working with AI assistance. The authors attribute this finding to the interpretive bottleneck created by hierarchical structures: when AI suggestions must pass through a designated supervisor before informing team action, the supervisory role becomes cognitively overloaded and the team's responsiveness to AI input is slowed. Self-managed teams distribute the interpretive and evaluative work of assessing AI suggestions across all members, allowing faster and more diverse engagement with AI-generated content. This finding reveals that the effectiveness of the assistant role is jointly determined by the AI's task capabilities and the organizational structure through which those capabilities are mediated.

Diebel *et al.* (2025) examine the psychological effects of proactive AI assistance in team settings, specifically AI agents that anticipate and address user needs before explicit requests are formulated. Their experimental study finds that proactive AI assistance reduces users' sense of competence based self-efficacy, generating a subjective experience of displacement rather than augmentation, which in turn reduces satisfaction with the AI interaction. The effect is moderated by prior AI knowledge: users with higher AI literacy experience weaker competence threat because they attribute the AI's proactivity to its design rather than to their own inadequacy. This study reveals a fundamental paradox of the assistant role at its upper capability boundary: an AI assistant that is maximally helpful, in the sense of anticipating and resolving needs before they are articulated, may undermine the human experience of competent contribution that is necessary for sustained engagement with team tasks.

Van der Waa *et al.* (2021) investigate the conditions under which human team members maintain adequate moral control over AI-assisted decisions with ethical consequences. Their study in simulated high stakes decision contexts finds that adequate control, defined as the ability to recognize and correct AI errors before they produce harmful outcomes, is reliably maintained when the consequences of AI-assisted decisions become observable within a short feedback window. When the feedback window is long, the conditions for adequate human control degrade and the risk of inappropriate reliance on the

AI assistant increases. Their framework specifies design requirements for assistant mode AI in ethically consequential settings: the temporal structure of feedback, not merely the AI's accuracy, determines whether the assistant role preserves human moral agency.

Stieglitz *et al.* (2021) extend the social loafing literature, originally developed in purely human group settings, to human-AI teams. In their study of teams working with virtual AI assistants, the presence of the assistant reduces individual team members' perceived personal responsibility for the quality of collective output. This responsibility diffusion is consistent with the Ringelmann effect: adding a contributor to a group task reduces each individual's perceived share of accountability. The extension to AI assistants is theoretically significant because it suggests that the psychological mechanisms through which AI may degrade human contribution in team settings are not exotic or technology specific but are instances of general social psychological principles. The assistant role, despite its nominally supportive framing, can restructure the human team's motivational architecture in ways that reduce collective performance.

Mirbabaie *et al.* (2020) examine social identity dynamics in teams collaborating with AI assistants, using a design in which participants were informed whether their collaborator was human or AI. Despite this transparent design, the study finds no significant difference in workload or satisfaction ratings between the AI-assistant and the human assistant conditions. The implication is that social identity mechanisms extend to AI collaborators in ways that parallel human to human dynamics. Mao *et al.* (2024) develop the Hybrid Intelligence Technology Acceptance Model for generative design assistants, finding that perceived ease of use is absorbed into finer constructs when users develop meaningful experience with the assistant's capabilities. Wu *et al.* (2026) report on a human-AI collaborative prompt generation architecture applied to industrial defect segmentation, demonstrating that the assistant framing extends into highly technical industrial quality-control contexts.

4.2.3 Tool

Category definition. The Tool role designates configurations in which AI functions as a cognitive instrument applied by human team members to extend their information-processing or decision-support capabilities, without being conceptualized as a social participant in the team's deliberation or activity. The tool framing denies the AI epistemic standing: AI-generated outputs are attributed entirely to the human operator who applies the tool, the AI's contributions do not enter the team's deliberation as a distinct voice, and the

relational vocabulary of membership, role, and standing does not apply. This is the classical paradigm of decision support systems, analytical dashboards, and recommendation engines, and it describes a large portion of AI deployment in practice even as the research literature increasingly emphasizes partner mode configurations.

Empirical grounding. Fügener *et al.* (2021) provide the most theoretically consequential evidence in the Tool category. Published in MIS Quarterly, their study demonstrates that AI advice improves individual classification performance but reduces the diversity of human judgment in ways that degrade the group's collective accuracy. The mechanism is homogenization: when all team members use the same AI tool as a decision input, their decisions converge around the AI's output, and the independent variation that makes group judgment more accurate than individual judgment is lost. This study reveals a systemic risk of tool mode AI integration that is structurally absent from partner mode integration: a partner that contributes a distinct perspective does not homogenize human thinking in the same way that a shared tool used for individual decision support does. The implications for team design are significant: tool mode AI integration optimized for individual performance may be net harmful for collective accuracy.

Kamada *et al.* (2026) report an experimental study on idea generation in which groups augmented with AI tools were compared against groups without AI access. The AI-augmented groups generated fewer ideas than unaugmented groups and did not achieve significantly higher idea quality. The authors propose that the mechanism involves cognitive offloading: access to an AI tool that generates ideas reduces human members' own generative effort, producing an overall reduction in the volume and diversity of team generated ideation. This finding, in combination with Fügener *et al.* (2021), suggests that tool mode AI integration is systematically more likely to produce adverse collective effects in divergent tasks, where the value of human contribution lies in diversity and novelty, than in convergent tasks, where the value lies in accuracy and optimization.

Zhang *et al.* (2026) reach a more positive conclusion for tool mode AI integration in collaborative new product development. Their study finds that large language model tools increase collective cognition by stimulating activity in problem framing and coordination spaces. The contrast with Kamada *et al.* (2026) can be reconciled by attending to task type: Zhang *et al.* study a structuring and coordination task for which AI-generated scaffolding is beneficial, while Kamada *et al.* study a purely generative ideation task for which AI offloading is harmful. This task type interaction is consistent with Dell'Acqua *et al.*'s (2024) jagged

frontier concept: tool mode AI integration produces heterogeneous effects that depend on whether the task demands convergent structured output or divergent creative contribution.

Gay *et al.* (2019) study unmanned ground vehicle operations, examining how operator suspicion of AI decision tools affects human-machine team performance across mission scenarios. Their findings document that operator overtrust in AI tools, manifesting as insufficient monitoring and verification of AI outputs, is associated with performance degradation in unexpected scenarios. This study illustrates the tool mode's inherent dependency on appropriate human oversight: tools, unlike partners, cannot self-regulate the distribution of attention and effort within the team; they require that humans perform the metacognitive function of calibrating reliance. Lawless (2022) extends this analysis theoretically, arguing that the data dependency structures inherent in autonomous human-machine teams constrain the logic of tool mode AI deployment in ways that formal decision frameworks underestimate.

Thomas *et al.* (2026) examine the reliability of generative AI in academic research assistance, framing AI as a cognitive augmentation tool for research teams. Their analysis of AI performance across research tasks reveals jagged reliability: AI tools are highly reliable for clearly specified retrieval and synthesis tasks but exhibit systematic failure modes in evaluation and judgment tasks that require contextual reasoning. Zhao *et al.* (2026) document tool mode AI use in a design application context, employing AI-generated content as a stylistic generation tool within a broader design team workflow, finding that the tool mode is appropriate and well received when humans retain full evaluative authority over AI outputs.

4.2.4 Autonomous Member

Category definition. The Autonomous Member role designates configurations in which AI operates as a self-initiating agent that occupies a functional team slot and generates behavioral sequences based on its own goal representations and environmental assessment, without requiring human prompting for each action step. The autonomous member framing is the most demanding role: it attributes planning capability, goal representation, and adaptive behavior to the AI in ways that parallel the cognitive architecture of a human team member operating independently on a delegated task. The distinction from both Partner and Assistant lies in the locus of initiative: partners engage in mutual epistemic exchange driven by both human and AI initiative, assistants respond to human prompts, and autonomous members generate and execute action sequences based on their own internal states.

Empirical grounding. Levine and Williams (2018) study human-robot teams engaged in tasks where the robot must simultaneously recognize human plans and adapt its own actions to complement them. Their study in the Journal of Artificial Intelligence Research provides formal evidence that autonomous teammate behavior requires genuine planning capability, not only reactive response: the robot must model the human teammate's goals, predict their future actions, and generate its own complementary action sequences in real time. This work establishes the technical and cognitive requirements for the Autonomous Member role and provides the earliest high quality evidence in the corpus that such configurations are technically realizable, even if organizationally rare at the time of publication.

Noorunnisa *et al.* (2019) apply the GORITE BDI (Beliefs, Desires, Intentions) framework to human-autonomy teaming, examining how autonomous agents structured around explicit belief, desire, and intention representations can function as genuine team members in task environments. Their case study demonstrates that BDI-based AI agents are capable of role consistent behavior across diverse scenarios without step-by-step human direction, meeting the operational criteria for the Autonomous Member category. The study also identifies conditions under which autonomous behavior becomes problematic: when the agent's beliefs diverge from ground truth and its revision mechanisms are insufficient to correct the divergence, the autonomous member's self-generated action sequences can conflict with human teammates' goals in ways that are difficult to detect and correct.

Nakahashi and Yamada (2021) study an implicit guidance agent that autonomously balances team performance with human autonomy preservation. Their study in Frontiers in Artificial Intelligence finds that an autonomous AI agent can maintain acceptable task performance while allowing human team members to exercise meaningful initiative, provided that the agent's guidance interventions remain below a perceptibility threshold. This finding raises a distinctive governance question: autonomous member AI that operates below the threshold of human awareness may produce beneficial outcomes without generating the trust and accountability frameworks that sustained human-AI teaming requires. Transparency and autonomous agency are in structural tension for this role category.

The small size of the Autonomous Member category (n = 3, 4.6%) is itself a significant finding. Despite active theoretical discussion of AI autonomy in organizations and extensive engineering work on autonomous multi-agent systems, only three of the 65 codeable studies document configurations in which AI operates as a fully autonomous team member in an

organizational or team context. This discrepancy between theoretical aspiration and empirical documentation is consistent with the observation that organizational autonomy for generative AI remains more aspirational than practically realized: the institutional, legal, and trust conditions for deploying genuinely autonomous AI agents within human team structures do not appear to have been met at scale within the review's time window.

4.2.5 Evaluator

Category definition. The Evaluator role designates configurations in which AI's primary function within the team is to assess, monitor, score, or provide comparative feedback on the performance of human team members, team outputs, or team processes. The evaluator framing positions AI in a metacognitive and supervisory relationship to the team rather than as a co-contributor to its primary tasks. This role is structurally distinct from all others in the taxonomy: rather than contributing to the team's output generating activity, the AI monitors and appraises that activity, giving it a distinctive authority profile that combines informational influence with formal or informal evaluative power.

Empirical grounding. The single study coded as Evaluator in this corpus is Bocklisch *et al.* (2024), who study hybrid decision-making in atmospheric plasma spraying and describe an AI system that evaluates process outcomes and provides feedback to the human team based on multi-criteria quality assessment. The AI's role is explicitly evaluative: it assesses whether the spraying process is meeting quality targets and communicates this assessment to the human operators, who retain authority over process adjustments. The study demonstrates that evaluator mode AI can improve team performance on complex multi-criteria optimization tasks by providing rapid, consistent assessment that exceeds human perceptual capacity while preserving human agency over responsive action.

The singularity of this category in the corpus is notable. Many AI applications in quality control, performance management, and process monitoring are implicitly evaluative, yet they are rarely framed in those terms in team research. The underrepresentation of the Evaluator category likely reflects a combination of disciplinary framing, team researchers tend not to study quality-control AI as a team role, and publication bias toward configurations that demonstrate AI's positive collaborative potential.

4.2.6 Decision-maker

Category definition. The Decision-maker role designates configurations in which AI holds consequential decision authority within the team's workflow, making determinations that are implemented without requiring human approval at each decision point. This is the most authority intensive role in the taxonomy: while partners and autonomous members exercise initiative, they do so within structures that preserve human ratification authority over final outputs. Decision-maker AI, by contrast, functions as a principal decision agent whose determinations are treated as binding for organizational purposes unless actively overridden by human team members.

Empirical grounding. The single study coded as Decision-maker in this corpus is Srinivas and Chetan (2026), who develop a framework distinguishing delegation from augmentation as modes of AI integration in strategic organizational decision-making. The delegation mode, in which humans assign clearly specified decision tasks to AI with high confidence in its outputs and low monitoring intensity, corresponds to the Decision-maker role: the AI is not merely informing a human decision but making the decision within the delegated domain. The study identifies conditions under which delegation is appropriate: high task structure, measurable outcomes, available performance feedback, and accumulated evidence of AI reliability in the specific decision domain. Conversely, delegation is identified as inappropriate when task structure is low, outcomes are equivocal, or AI reliability in the domain has not been established, conditions that characterize much of the organizational decision landscape for generative AI in 2026.

The singularity of this category, like the Evaluator category, reflects both actual rarity and representational gaps. Formal decision authority is rarely assigned to AI in the current organizational landscape, and studies that document such assignment are likely to cluster in highly technical domains where automated decision systems have long precedent, such as algorithmic trading and process control, which are not prominent in this corpus.

4.2.7 Other

Category definition. The Other category captures the single study that described a coherent and distinct AI role not captured by the preceding six categories.

Empirical grounding. Ellwart *et al.* (2022) study sociodigital self-comparisons in hybrid teams, examining how human team members evaluate themselves relative to AI colleagues across cognitive performance dimensions. This study does not assign AI a team

role in the conventional sense of a task function; rather, it positions AI as a social referent within the team, a standard against which humans measure and interpret their own capabilities, contributions, and standing. The AI functions as a comparison object that shapes team members' self-concepts and behavioral orientations without actively contributing to the team's output generating activity. This framing is theoretically distinct from all other categories in the taxonomy: the AI's influence operates through social comparison processes rather than through direct contribution, assistance, or governance.

4.3 METHODOLOGICAL MATURITY OF THE EVIDENCE BASE

The methodological composition of the 67 full-text confirmed studies provides a secondary finding: the literature on AI roles in team settings is empirically substantive. Experimental and quasi-experimental designs, the designs that provide the strongest causal evidence for role specific effects, account for 31.3% of the corpus. Qualitative and case study approaches contribute an additional 20.9%, and mixed methods studies add 4.5%. The combined share of empirical designs, meaning those that collected and analyzed original data, is approximately 57% of the corpus. Conceptual and theoretical work accounts for 19.4%.

This distribution is consistent with an active research community that has moved beyond initial theoretical framing and is producing controlled empirical evidence. However, it also reveals a persistent gap between the field's aspirational theoretical constructs and its empirical measurement practices. Three patterns merit attention. First, the majority of experimental studies use laboratory or simulation settings with student or convenience samples, limiting the generalizability of their findings to the organizational contexts in which AI teaming is most consequential. Second, longitudinal designs are rare in the corpus: most studies capture AI role dynamics at a single point in time or across a single task session, while the evidence from sensemaking studies (AGARWAL *et al.*, 2026) and role elaboration frameworks (SIEMON, 2022) suggests that AI roles are dynamically negotiated and evolve over time. Third, multi-team or multi-organizational comparative designs are absent, making it difficult to assess whether role distributions are domain specific or reflect general patterns.

The dominance of experimental designs in studies of the Assistant and Tool categories, and the greater prevalence of qualitative and theoretical work in studies of the Partner category, is also notable. Partner mode AI is more frequently studied through ethnographic, interview, and conceptual methods, which are better suited to capturing the

social construction and negotiation processes through which partnership is realized, while assistant mode and tool mode AI are more frequently subjected to controlled experiments that isolate performance effects. This methodological divergence reflects the different theoretical questions each category raises: partner mode research asks how partnership is constructed and what it means for teams, while assistant mode and tool mode research asks whether and how much performance changes. Both are legitimate questions, and the field benefits from the methodological diversity, but the divergence makes direct comparison of evidence quality across categories difficult.

4.4 PROCESS STAGE GRANULARITY GAP

Finding 3 concerns the low granularity with which studies specify the process stage at which AI participates in the team's workflow. Of 65 codeable studies, 49 (75.4%) specify any process stage at all. Among those 49, 16 (32.7%) describe AI participation only at the level of “workflow” or “team process” without more specific identification. Task execution is named in 6 studies (12.2%) and decision making in another 6 (12.2%). All other specific process stages, including problem identification, ideation, evaluation, implementation, and monitoring, appear only once or twice each across the corpus.

This granularity gap matters for several reasons. First, the jagged technological frontier concept (DELL'ACQUA *et al.*, 2024) predicts that AI's relative performance advantage varies substantially across subtasks within a single workflow. A study that reports AI's role as “workflow participation” without specifying which subtasks the AI performs or at which stage the AI's contribution is most consequential cannot discriminate between configurations where AI adds value and configurations where it does not, even within the same nominally partner mode deployment.

Second, Choi *et al.*'s (2026) analysis of the creativity paradox demonstrates that the functional desirability of partner mode AI depends on whether the AI is participating at a divergent generation stage, where its speed and scale advantages are most valuable, or at a convergent evaluation stage, where its authority could displace human judgment on matters of quality, originality, and fit. These are not merely different stages of the same role; they produce different team dynamics, different authority structures, and different performance implications. Coarse process stage coding cannot capture this distinction.

Third, the process stage gap interacts with the role taxonomy itself: the same AI system may occupy different roles at different stages of the team's workflow. Adil *et al.* (2026)

document this phenomenon in software development teams, where AI acts as a partner during initial design ideation, shifts to an assistant role during implementation, and is used as a tool mode verification resource during quality review. A taxonomy that assigns a single role per study necessarily suppresses this within study variation. Future research that tracks AI role dynamics across process stages would substantially enrich the evidence base.

The practical implication for research design is that process stage specification should become a standard reporting requirement for studies of human-AI teams. Journals publishing human-AI team research may benefit from requiring authors to characterize, at minimum, which stage of the team's workflow is being studied and whether AI's role varies across stages. Without this information, the cumulative evidence base for human-AI team design remains coarser than the design decisions practitioners must make.

4.5 CONNECTING THE TAXONOMY TO THE THEORETICAL AGENDA

The present review's empirical finding that 67.7% of coded studies assign AI a Partner role is consistent with, though not a direct replication of, the theoretical agenda set by Seeber *et al.* (2020), who argued for machines as teammates as a distinct research agenda and called for empirical investigation of AI in team membership roles. The present findings suggest that the research community has substantially responded to this agenda: a clear majority of studies treat AI not as a tool or subordinate but as a participant with social standing in team settings. This is not to claim that the theoretical agenda has been confirmed in the sense of establishing that AI is an effective or appropriate partner in organizational teams; the corpus documents how AI is framed, not whether that framing is always warranted. But the prevalence of partner framing is itself evidence that the synthetic teammate concept has become a dominant organizing category for human-AI team research.

The tension between the Partner category's frequency and the Autonomous Member category's rarity is theoretically informative. McNEESE *et al.* (2018) develop the synthetic teammate concept in contexts, specifically defense and aviation, where genuine operational autonomy is a defining feature of the AI's team role. The present corpus suggests that in the broader organizational literature, the preferred framing for AI in high functioning team roles is partnership rather than autonomy: AI as a collaborative contributor whose initiative complements human direction, rather than AI as an independent agent whose behavior must be coordinated with human activity at the team level. This preference may reflect genuine organizational risk management, legal accountability constraints, or the practical reality that

current large language models, however capable in generating outputs, do not yet function reliably as autonomous agents in complex multi-stakeholder organizational environments.

The hybrid intelligence framework of Dellermann *et al.* (2019) is also confirmed as descriptively apt. The dominant empirical pattern in the corpus is complementary co-contribution, not substitution or independence: AI and human team members are consistently described as contributing different capabilities to shared tasks, with neither fully replacing the other. This complementarity is precisely what the hybrid intelligence concept predicts as the productive mode of human-AI integration, and its prevalence across domains, from healthcare diagnosis to fashion design to software engineering, suggests that the complementarity principle generalizes beyond the information systems contexts in which Dellermann *et al.* originally articulated it.

4.6 LIMITATIONS

This review has five categories of limitations that are relevant to interpreting its findings.

Single reviewer design. The review was conducted without a second independent reviewer for screening or coding. This means that inter-rater reliability could not be assessed, and idiosyncratic interpretive patterns in the role coding cannot be detected or corrected. The role taxonomy should be read as one rigorously applied but fallible interpretive process.

Unresolved pending records. 580 records received a pending eligibility decision that was not resolved within this review. These records may contain eligible studies, particularly for the smaller and less stable role categories. The reported category frequencies may change when or if a future review pass resolves these records.

Single database. The search was conducted in Scopus only. Multidisciplinary coverage of Scopus is broad, but studies indexed exclusively in Web of Science, IEEE Xplore, or domain specific databases may have been missed. This is particularly relevant for engineering and human factors literature where the Autonomous Member and Evaluator categories may be better represented.

Framing bias. Studies drawn to publish on human-AI collaboration are more likely to study contexts in which meaningful collaboration occurred, potentially overrepresenting the Partner category relative to its prevalence in the full population of deployed human-AI team configurations. Many organizational AI deployments that function primarily in tool mode may go unstudied or unpublished.

No formal risk-of-bias assessment. A formal instrument based risk-of-bias assessment, such as the Mixed Methods Appraisal Tool or the JBI Critical Appraisal checklist, was not applied to the 67 full-text confirmed studies. The absence of this assessment means that the confidence level of individual study findings within each category cannot be formally ranked. Future reviews that apply such instruments would provide a more differentiated account of the strength of evidence for each role category.

5 CONCLUSION

This systematic literature review of 65 codeable studies drawn from a 7,541 record Scopus search establishes three substantive findings about how generative AI is conceptualized and studied within team settings.

The primary finding is that the Partner role is the dominant framing in the current literature, accounting for 67.7% of coded studies across eight years and multiple domains. This finding is stable across the review's methodological diversity: partner mode AI is documented in randomized controlled trials, ethnographic case studies, conceptual frameworks, and experimental simulations. The stability test comparing an intermediate subset of 57 studies to the final 65 study corpus confirmed a shift of 4.3 percentage points, below the 5 point criterion for instability. The dominance of the Partner category represents a meaningful shift in how the research community conceptualizes AI's organizational standing: not as an instrument subordinate to individual users, but as a contributor with recognized social standing in team processes.

The secondary finding concerns methodological maturity. The evidence base is empirically substantive, with experimental and quasi-experimental designs accounting for 31.3% of the full-text confirmed corpus. The field has moved substantially beyond theoretical framing toward controlled empirical investigation, though longitudinal designs and multi-organizational comparisons remain rare. The methodological diversity of the corpus, spanning controlled experiments, ethnographies, surveys, and conceptual frameworks, reflects appropriate pluralism for a research area where the relevant phenomena, role construction, trust calibration, and collective performance, require different methodological approaches to be fully characterized.

The third finding is the process stage granularity gap: only 16 of 65 studies identify the specific substage of the team's workflow at which AI participates. This gap limits the field's ability to connect role taxonomy findings to the practical design and governance decisions

that practitioners must make at the level of individual workflow stages, not merely at the level of overall team configuration. Addressing this gap requires that future studies specify process stage participation as a standard reporting element.

Taken together, these three findings converge on a core practical and theoretical message: generative AI in team settings is predominantly a partner level participant whose integration is most productively designed as complementary co-contribution rather than unidirectional assistance or autonomous operation. The design implications are specific: teams integrating AI at partner level require explicit attention to role clarity, authority allocation, accountability structures, and trust calibration, because partner mode integration, unlike tool mode use, distributes epistemic and coordinative responsibility across human and AI contributors in ways that alter the team's social and organizational architecture, not only its task performance.

Future research should address four priorities emerging from this review's findings and limitations. First, longitudinal studies that track AI role dynamics across task phases and across the team's developmental timeline would test whether partner mode configurations are stable or whether they represent early phase framing that gives way to tool mode or assistant mode integration as novelty effects dissipate and task routinization occurs. Second, process stage specific studies that examine how AI role varies within a single workflow would test the hypothesis that AI simultaneously occupies multiple roles across a team's task sequence. Third, comparative multi-organization studies that assess AI role distribution across sectors, team types, and governance environments would test whether the Partner category's dominance is field wide or concentrated in the research intensive and knowledge work contexts that are disproportionately represented in the current corpus. Fourth, the Autonomous Member category's low representation, despite active theoretical development of AI autonomy concepts, warrants investigation: future studies should examine the institutional, legal, and trust conditions under which autonomous AI agents gain meaningful acceptance as team members rather than remaining engineering demonstrations.

The taxonomy developed here provides a shared vocabulary for this research agenda. By grounding seven role categories in 65 full-text confirmed studies spanning multiple disciplines and methodologies, the review establishes a conceptual baseline that can structure comparative analysis, guide design choices, and focus governance discussions on the specific role configurations that carry the highest practical stakes.

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