ITAIS 2024 Proceedings

Annual conference of the Italian Chapter of AIS (ITAIS)

Winter 12-11-2024

From a Task-Centered Approach to Interdependent Activities: Revealing Gaps in Generative AI Research on Coordination and Cooperation

Francesco Bolici

Alberto Varone

Gabriele Diana

From a Task-Centered Approach to Interdependent Activities: Revealing Gaps in Generative AI Research on Coordination and Cooperation

Francesco Bolici[1[0000-0002-8532-4981]], Alberto Varone[1[0009-0005-6900-0839]] and

Gabriele Diana[1[0000-0001-6811-3982]]

[1] University of Cassino and Southern Lazio, Loc. Folcara, Cassino 03043, IT
f.bolici@unicas.it
alberto.varone@unicas.it
gabriele.diana@unicas.it

Abstract. Generative AI is bound to have profound effects over work and how it is organized. However, while existing research has focused on uncovering the impact of Generative AI systems on the execution of individual tasks, it has significantly under-emphasized the interdependent and collaborative nature of work. To support filling this gap, this paper investigates the implications of generative AI on collaborative work activities, emphasizing the need for a shift from a task-centric approach to a broader process-oriented perspective. By utilizing the 3C collaboration model—communication, coordination, and cooperation—this study employs a bibliometric-based analysis to map the current state of research in this domain, identifying gaps and opportunities for field development. Our analysis identifies significant disparities in academic focus on Generative AI in collaborative settings, highlighting under-researched areas such as cooperation and coordination. Moreover, research in the domain of collaboration is remarkably segregated, with few studies addressing multiple collaboration dimensions simultaneously. Lastly, while there is a strong emphasis on Human-AI interactions, the role of AI in mediating Human-Human interactions is less explored. Addressing these gaps could provide valuable insights into defining strategies to effectively integrate generative AI systems within complex organizational settings.

Keywords: Generative AI, LLMs, ChatGPT, Collaboration, Coordination.

1 Introduction

The diffusion of disruptive technologies is reshaping work, prompting organizations to reassess their fundamental assumptions and work practices [1, 2].

Generative AI exemplifies this trend [3], and can be defined as a class of machine learning models that can generate new data rather than merely making predictions or classifications [4]. Thus, unlike traditional AI, Generative AI exhibits creativity and originality to some degree [2, 5]. The economic impact of these systems is projected to be between $2.6 and $4.4 trillion annually [6], disrupting occupations and task compositions [7] particularly in customer operations, marketing, sales, software engineering, and product R&D [6, 8].

The record-breaking diffusion of ChatGPT [9], a revolutionary AI chatbot [1, 10], has popularized generative AI systems in both media discussions and research. Since then, research on generative AI applications has blossomed across various domains. In the realm of software development, Tufano et al. [11] tested the performance of generative AI on various tasks, including feature implementation/enhancement, documentation, learning, automating commits/issues/pull requests, software quality, development environment, and data manipulation, resulting in notable productivity gains at the developer level. Peng et al. [12] evaluated generative AI's impact on general productivity in software development, finding the most substantial benefits among less experienced programmers. Kocoń et al. [13] tested ChatGPT's performance on 25 different Natural Language Processing (NLP) tasks, including semantic and emotion-based tasks, and observed a 25% average quality loss compared to state-of-the-art models, with higher complexity tasks showing greater deviation. Noy and Zhang [14] examined generative AI's use in mid-level professional writing tasks, focusing on idea generation, editing, and reducing rough drafting efforts. Lim and Perrault [15] explored idea generation in collaboration with AI (co-GPT ideation) and discovered that the generated ideas were more unique and of higher quality compared to solo efforts. Brynjolfsson, Li, and Raymond [8] assessed generative AI's impact on customer support tasks by measuring customer satisfaction and the number of issues resolved per hour, finding significant improvements in both areas. Lastly, Dell'Acqua et al. [16] tested generative AI in consultancy, revealing significant enhancements in task performance and quality within the AI's capability frontier.

Despite strong research emphasis on generative AI performances in supporting human workers in accomplishing individual tasks, we argue that, in organizations, tasks rarely occur in isolation [17]. Instead, they are part of more complex organizational processes, where tasks are interdependent and require cooperative, communicative, and coordinated efforts to be effectively executed [18]. In this context, the role of humans is not only to perform these tasks but also to coordinate them by managing their interdependencies [17, 18]. Despite the importance of these organizational dynamics, research on this topic is currently under-emphasized [19]. Thus, a research gap exists in understanding how to incorporate Generative AI capabilities and tools within work environments characterized by significant task interdependencies, and how the structure and coordination of work activities will change with the implementation of such disruptive systems [19].

To support filling this gap, this work assesses the current state of research on the implications that generative AI will have on collaborative work activities. Adopting the 3C collaboration model as our theoretical framework, we implement a bibliometric-based analysis that considers the theme of collaboration and its constituent dimensions: communication, coordination, and cooperation. After implementing a contextual and historical analysis of the research scenario, our goal is to assess the state of advancement in each of the above-mentioned fields, their thematic compositions, and cross-sections to identify research gaps and opportunities for future research. Accordingly, the research question we aim to answer is: what research gaps undermine a more practical comprehension of generative AI implications on collaborative work activities in terms of communication, coordination, and cooperation? We argue that this mapping activity has at least two main advantages: first, it brings the study focus to broader organizational activities rather than individual tasks, which are more typical of real-world organizations. Second, it provides directions for developing currently less emphasized research streams, which is of paramount importance for actual generative AI applications in organizational contexts.

2 Theoretical Background

2.1 3C collaboration model

This study aims to investigate the implications of generative AI deployment on collaboration, communication, cooperation, and coordination. For this purpose, we adopt the 3C Collaboration Model as a theoretical framework, which draws from managerial, social psychology, group behavior theories, and behavioral science [20, 21].

The 3C Collaboration Model is originally a model for the analysis, representation, and development of "groupware" [22]. The model was originally developed by [23] which defined groupware as "computer-based systems that support groups of people engaged in a common task (or goal) and that provide an interface to a shared environment" [23], reflecting a shift from using computers to solve problems to using computers to facilitate human interaction [20, 23].

According to its original conceptualization, the 3C model emphasizes communication, collaboration, and coordination [23]. Specifically, the model posits that effective collaboration requires individuals to share information necessary to work together towards achieving a common goal or activity. Drawing from Coordination Theory, defined as the body of principles about "how activities can be coordinated, that is, about how actors can work together harmoniously" [17], Ellis et al. [23] emphasizes the centrality of effective coordination as the activity that enhances communication and collaboration among group members. According to Coordination theory [17], coordination has three main components: activities, actors and interdependencies. Thus, coordination is defined as the act of managing interdependencies between activities performed to achieve a goal [17]. Importantly, and consistent with the primary focus of [22] as well as the postulates of Coordination Theory [17, 18], this study refers to dependencies as arising between tasks rather than individuals or units.

A significant evolution of the 3C Collaboration Model was implemented by Fuks et al. [22]. The most notable variation from the original model is that what Ellis et al. [23] termed "collaboration" was reconceptualized by Fuks et al. [22] to characterize joint operation in a shared space. Thus, in the most widespread form, the 3C Collaboration Model posits that collaboration emerges from iterative cycles of communication, coordination and cooperation [22, 24]. More specifically, while communicating, people negotiate and make decisions. While coordinating, they handle conflicts and organize their activities to prevent the loss of communication and cooperation efforts. Cooperation involves the joint operation of group members in a shared space, seeking to execute tasks, generate and manipulate cooperative objects. When unexpected situations arise requiring renegotiation and decision-making, a new round of communication may be necessary. This, in turn, requires coordination to reorganize the tasks that need to be carried out during cooperation [22, 24, 25].

The 3C Collaboration Model has been extensively studied and applied to understand collaborative dynamics in various domains. These include collaborative software development, both intended as a specification of Computer Supported Cooperative Work (CSCW) [20] and in studying collaborative learning dynamics within FLOSS communities [26], in emergency management [27], healthcare (in an adapted framework focusing on communication, confidence, and continuity of care) [28], and business, where it addresses the effects of trust and relationship commitment among SMEs on communication, cooperation, and coordination performance and satisfaction [29].

The model has primarily been used for designing and implementing collaborative systems [26, 30–32]. Its application as a theoretical basis for literature review studies is also recognized [27, 28]. Additionally, studies have demonstrated that the criteria defined by the 3C model can be mapped as parameters for classifying interactive tools used in virtual environments [33].

2.2 Diffusion of Innovation Theory

Generative AI is a relatively new technological system that gained popularity following the release of ChatGPT in November 2022 [4]. Despite its recent emergence, it demonstrated potential for dramatic diffusion [9]. Accordingly, in order to contextualize key terms in this study, it is necessary to provide a theoretical overview of key concepts related to innovation and innovation diffusion dynamics. To achieve this, we refer to Rogers' Diffusion of Innovation Theory [34].

Innovation diffusion refers to “the process by which an innovation is communicated through certain channels over time among the members of a social system” [34]. In turn, innovation refers to an idea, practice, or object that is perceived as new by its adopters, where newness can be expressed in terms of knowledge, persuasion, or a decision to adopt [34].

Innovations diffusion follows a cumulative normal distribution pattern [34]. Initially, the curve exhibits a gradual incline, representing the slow adoption rate among early innovators. This phase is characterized by limited uptake and minimal social influence. As the innovation gains traction, the curve enters a period of rapid acceleration, signifying widespread adoption across broader segments of the population. Finally, the curve's gradient decreases, approaching an asymptote as the innovation reaches market saturation.

Innovation diffusion is remarkably socially shaped. Social factors influencing innovation diffusion include social contagion, structural equivalence, prestige, spatial proximity, culture, and social pressure [35–38]. These factors represent mechanisms to manage the uncertainty associated with the perceived newness of the innovation.

Moreover, influential individuals may further contribute to the determination of innovation diffusion patterns [34]. Among these, a common distinction is made between opinion leaders, capable of frequently influencing others’ behaviors, and opinion brokers, who fill structural holes in the network, connecting otherwise loosely connected groups [34, 39–41].

3 Methods

This study aims to investigate the implications of generative AI deployment on collaboration, communication, cooperation, and coordination, which represent crucial dynamics in real organizational environments [18, 19].

To achieve this goal, we adopt a bibliometric-based approach, suitable for the historical, thematic, and comprehensive review of a high volume of scientific publication data [42]. The dataset analyzed in this study was collected using the Scopus API. Scopus is one of the most prominent repositories of scientific papers and is among the most commonly used data sources for bibliometric-based research due to its extensive data availability [43–45]. The search query was designed to mine data from all scientific papers that contained either "generative artificial intelligence" or "large language models" and at least one of "communication," "collaboration," "coordination," or "cooperation" within the title, abstract, or authors' keywords. The combination of keywords chosen aligns with the 3C Collaboration model [22, 23], which we adopt as the theoretical foundation of this work.

Metadata was extracted on June 4, 2024, resulting in the acquisition of data on 889 publications. As the Scopus keyword search automatically considers both authors' keywords and keywords indexed by Scopus, it was necessary to filter out contributions that did not satisfy our inclusion query. This filtering process led to the exclusion of 163 documents that did not contain any of the desired strings (collaboration, cooperation, communication, or coordination) within their title, abstract, or authors' keywords. Consequently, 726 observations were retained.

After data cleaning, we conducted a comparative historical analysis to investigate the growth trajectory of the four research domains considered. This was followed by an analysis of keyword co-occurrence in each of the four domains, implementing a science mapping-based approach [42]. To achieve this aim, each contribution was assigned to one or more of the four subsets based on the keywords they discussed. Papers discussing more than one keyword were assigned to multiple datasets. The purpose of this division is to provide a comparative thematic analysis of each distinct dimension of collaboration, including the comprehensive term itself and its components (communication, coordination, and cooperation).

Network data were clustered using the algorithm developed in [46], which is well-suited for community detection in large networks. The software we utilized for network analysis is Gephi. We considered the five largest clusters in terms of keywords for interpretation. Interpretation of the community thematic composition is based on keyword presence and degree centrality, measured by the number of direct neighbors of a node (i.e., its number of connections) to emphasize their level of connectedness within the research domain. The higher the centrality, the more often a node has been quoted with other keywords in the network [47]. Lastly, we utilized a Venn diagram to represent areas of interaction among the four analyzed areas. This was operationally executed by combining titles, abstracts, and authors' keywords into a single string for each contribution, which was then lowercased to support text homogenization.

An overview of the number of publications, authors, and the time span of research in each of the domains analyzed is provided in Tab. 1. Communication attracted the highest number of contributions (450) and authors (1,883), indicating a strong research focus. Collaboration also has significant research activity with 280 documents and 1,127 authors. Cooperation and coordination have fewer documents and authors, suggesting these areas are less explored. The time span of analysis is relatively short, highlighting the newness of the technology analyzed in this study.

In compliance with ethical research standards, we disclose the use of ChatGPT for proofreading this work. All of the content generated was reviewed and, when necessary, further edited by the authors, who take full responsibility for the content of this work.

Table 1. Data Overview

Domain	Time span	Publications	Authors
Cooperation	2023 - 2024	29	158
Communication	2021 - 2024	450	1883
Coordination	2023 - 2024	26	117
Collaboration	2022 - 2024	280	1127

4 Results

4.1 Historical Analysis

The historical analysis (Fig. 1) highlights a dual development trajectory in academic research on Generative AI and its consequences for collaboration. While collaboration and communication-focused research experienced a strong boom, cooperation and especially coordination have been under-emphasized. These trends suggest the presence of a gap in research and an opportunity to further develop the field.

In particular, research focused on communication experienced exponential growth, particularly from 2022 onwards, increasing from 2 publications in 2021 to 9 in 2022, and then sharply rising to 211 in 2023 and 228 in the first months of 2024. Similarly, collaboration-focused research saw a dramatic growth, from 12 publications in 2022 to 139 in 2023, with 129 publications in the first months of 2024. In contrast, the number of publications related to cooperation remained relatively low and stable, with a slight increase from 14 in 2023 to 15 in the first months of 2024. Coordination followed a similar pattern, with 14 publications in 2023 and a slight decrease to 12 in the first months of 2024. These trends suggest consistent but relatively marginal interest over the latter two dimensions.

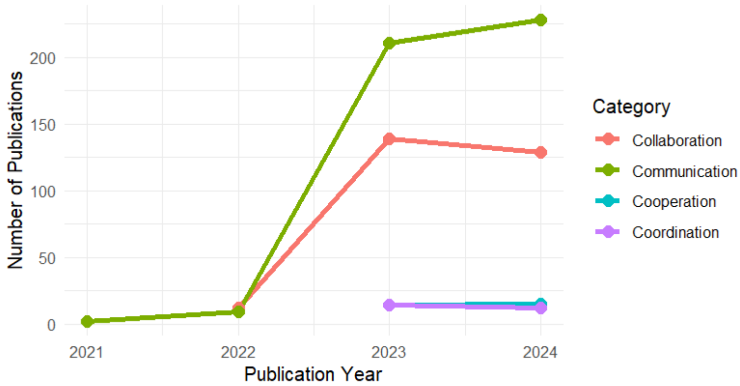

Fig. 1. Publication trends over time

4.2 Analysis of the individual dimensions: collaboration, communication, cooperation and coordination.

Collaboration. The collaboration network is the second largest among the four analyzed in this study, representing a total of 4,476 links among 845 keywords. Apart from keywords like “Generative AI”, “LLM”, and “collaboration,” which were central by methodological design, the most central keywords under the dimension of degree centrality are human-AI collaboration (degree of 72), education (65), algorithms (47), and ethics (39). The centrality of human-AI collaboration underscored AI's role in supporting human capabilities in diverse contexts, including education, healthcare, and creative industries.

Cluster 1 emphasizes a strong research attention on the domains of education and academia, with a particular focus on ethical considerations. Within the education domain, keywords such as "education" (degree of 65), "higher education" (42), "educational technology" (30), "teaching" (27), "learning" (25), and "entangled pedagogy" (13) are prominent. Academia is represented by keywords like "authorship" (27) and "academic writing" (25), while ethical considerations are highlighted by "ethics" (39), "academic integrity" (28), and "transparency in research" (25). Additionally, this cluster explores broader concepts of intelligence in the collective realm, such as "collective intelligence" (10), "collective superintelligence" (10), "swarm AI" (10), "swarm intelligence" (10), and "co-creating" (25). Although less significantly, it also delves into collaborative activities like "deliberative problem solving" (10) and performance outcomes such as "productivity" (9).

Cluster 2 focuses on infrastructural and operational aspects of AI deployment. Key terms include "human-computer interaction" (15), "human-centered artificial intelligence" (12), and "human-AI interaction" (11), reflecting the emphasis on human-AI collaboration. The infrastructural and operational aspects are highlighted by terms like "software architecture" (16), "multi-agent collaboration" (13), "training" (20), and "explainable artificial intelligence (XAI)" (18). Foundational concepts related to knowledge management are also discussed, with keywords such as "knowledge" (27), "DIKW hierarchy" (18), and "information" (18). Despite having lower centrality, the domains of education and medicine, emphasizing the field of psychology, are present also in this cluster. Keywords such as "AI in education" (15) and "GAI-assisted learning (GAIAL)" illustrate the relevance to education, while "medicine" (14), "psychological healing" (10), and "emotional aids" (10) indicate the significance of AI in healthcare. Other central domains of application include "social media" (18) and the "metaverse" (13), with activities like "design" (14) and "personalization" (14) also being prominent. Behavioral dynamics discussed in this cluster include "empowerment" (10) and "AI trust" (9).

Cluster 3 emphasizes research on the implications of AI-generated content for collaboration in creative and artistic activities. This is highlighted by the centrality of keywords such as "artistic research" (12), "generative art" (9), "music composition" (3), "creativity support" (10), "creativity" (8), and "creative writing" (7). Additionally, Cluster 3 emphasizes several concepts associated with design activities, including "novice designers" (5), "personas" (5), "AI-assisted design" (5), "avatar design" (5), and "product design" (4), with some emphasis on business modeling, with "intergenerational design" (9). Legal domains also appear in this cluster, with terms such as "criminal law" (5) and "empirical legal studies" (5) being included in the debate.

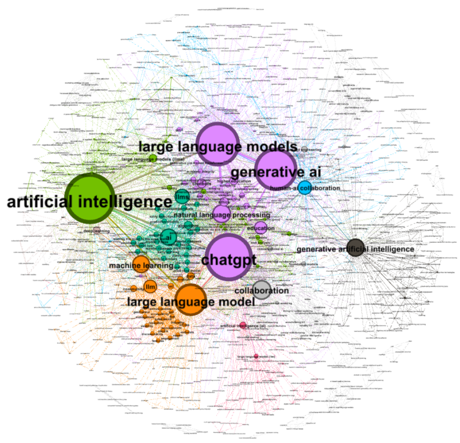

Fig. 2. Collaboration network

Cluster 4 is distinctive for its focus on virtual and augmented workplaces. Key terms in this cluster include "virtual immersive workspaces" (7), "workplace collaboration software" (6), "immersive remote collaboration" (6), "3D virtual simulation technologies" (7), "ambient scene detection" (7), "visual data mining" (7), "virtual reality immersive training tools" (5), "immersive work" (5), "wearable augmented reality devices" (5), and "extended reality" (5). This cluster also covers various organizational dimensions connected to control, such as "algorithmic monitoring" (10) and "virtual team movement and behavior tracking" (4). It further explores mentorship ("mentorship" (6)), communication ("virtual communication and collaboration tools" (4)), performance ("virtual team performance tools" (5)), and engagement ("virtual employee engagement" (6)). Within this broad domain, specific references are made to "remote collaboration" (11), "decentralized autonomous organization" (7), and "adaptive self-organizing systems" (5). Ethical issues connected to these topics are also mentioned, with themes such as "discriminative AI" (7), "ethical AI" (7), and "ethical issues in AI" (4).

Cluster 5 is centered around the keywords "innovation" (35), "industry" (30), and "management" (26), drawing a connection with generative AI attributes such as "accessibility" (26), "discoverability" (26), and "usability" (26). This cluster also highlights outcomes like "engagement" (26), "enhancements" (26), and "improvements" (26), emphasizing the role of generative AI in driving progress.

Communication. Communication is the largest network among the ones analyzed, representing 1,348 keywords connected by 7,902 links. Similar to the Collaboration network, central research domains in the Communication realm emphasize healthcare and education

These themes find particular traction in Cluster 1, which emphasizes the transformative potential of AI in healthcare and medical settings, both in terms of Human-AI interactions and AI-mediated Human-Human communication through content simplification and customization. The primary forms of communication addressed are related to education and patient-physician interactions. This is evident from the centrality of themes like medical education (70), educational technology (31), and human-machine interaction (26) for education. For patient-physician communication, the central themes include patient-physician communication (21), doctor-patient interaction (16), and patient-provider interaction (11). Moreover, the analysis provides evidence that written communication is currently particularly central in generative AI medical research, with terms like transcript (20), transcripts (20), and medical documentation (20) occupying central positions in the network. Technical attention is also given to Human-machine communication, as indicated by the presence of human-computer interaction (26) and human-machine interaction (26). Cluster 1 also references human and ethical aspects of communication, notably empathy (11), bias (13), and AI ethics (9). At the technological level, Cluster 1 mentions virtual reality, having a centrality score of 22 in the network.

Cluster 2 deepens the topics researched in the first cluster, with specific attention to technology-enabled and personalized forms of healthcare. High centrality is attributed to terms such as "digital health" (46), "mobile health" (34), "mHealth" (32), "customization" (30), "customize" (23), "customized" (23), and "behavior change" (27). Additionally, this cluster highlights attributes of creativity, with keywords like "creativity" (33) and "creative" (23), and the concept of collective intelligence (11). Although marginal, there is some centrality visible for technologies like computer vision (9) and prompt-engineering (5).

Cluster 3 emphasizes research interest in digital and technological innovation, such as "augmented reality" (20), "robotics" (20), and "AI agent" (8), in the macro area of augmented communication (8) and collaborative work (8). This cluster addresses domains like scientific communication (12), focusing on keywords like academic publication (11), AI-assisted review (11), peer review (11), and marketing-related forms of communication, such as computational advertising (6) and digital advertising (6).

Cluster 4 delves into the technical underpinnings of AI system development. Central keywords in this cluster include "semantics" (31), "semantic communication" (28), "training" (56), "codes" (15), "training data" (13), cognitive development (11), humanoid robots (11) and "communication systems" (10). Algorithms like image reconstruction (17) and emotion recognition (15) are also highlighted. This cluster places peculiar emphasis on security in the association between generative AI and communication, addressing themes such as "security" (30) and "data privacy" (25). Additionally, this cluster refers to the higher-order concept of collaboration, attributing a degree centrality of 13 to this term and 12 to "collaborative inference" (12).

Lastly, Cluster 5 attributes the node with the highest centrality to "prompt engineering" (48). This cluster also focuses on aspects related to data transmission, such as "AI-integrated traffic information system" (8) and "traffic data processing" (8). Additionally, it highlights the importance of "social media" (20) and "social communication" (8), as well as "nonverbal communication" (11).

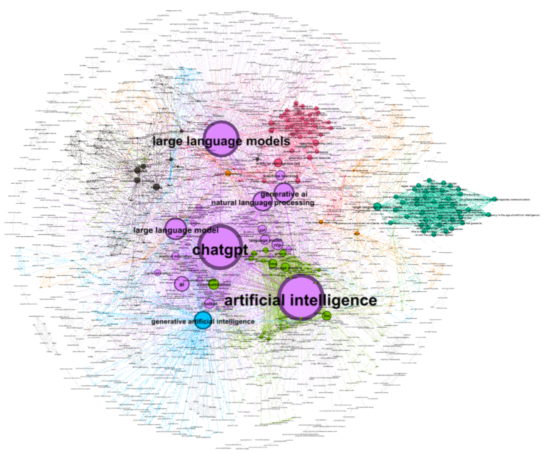

Fig. 3. Communication network

Cooperation. The cooperation network is the third in terms of size expressed in terms of number of keywords represented (101) and links among them (400), significantly smaller with respect to collaboration and communication networks. The cooperation network reflects diverse applications and challenges of AI in fostering cooperation, from technical and ethical considerations to interdisciplinary approaches and societal impacts. This research network emphasizes ethical and responsible AI practices, prominently featured in Clusters 2 and 4, with keywords like "ethical AI" (15 in Cluster 2) and "consumer protection" (4 in Cluster 4), highlighting the need for transparency, accountability, and ethical considerations in AI deployment. This aligns with the broader goal of ensuring that AI systems are not only effective but also trustworthy and aligned with human values.

Cluster 1 emphasizes the dimension of safe AI use, highlighting terms such as "data privacy" (20), "cybersecurity" (4), and "security development" (4). Additionally, technical dimensions are discussed, including "computational modeling" (12), "edge intelligence (EI)" (12), "fine-tuning" (12), "inference algorithms" (12), "resource allocation" (12), "resource management" (12), and "systems architecture" (12).

Cluster 2 is a niche specification of Cluster 1. It addresses the operational and ethical challenges of making AI systems interpretable and responsible. Some significantly central keywords in this area are "explainable artificial intelligence" (15), "XAI" (15), "concept-based explanations" (15), "responsible AI" (15), "ethical AI" (15), "falsifiability" (15), "interdisciplinarity" (15), "interpretability" (15), and "trustworthy AI" (15). The discussion also considers open challenges (15) to facilitate better human-AI cooperation by enhancing user understanding and trust.

Cluster 3, 4 and 5 contains keywords of marginal centrality in the network. Cluster 3 integrates concepts from Artificial Life (5) and game theory, quoting ideas such as "prisoner's dilemma" (5) and "personality trait" (5). Cluster 4 highlights the transformative potential of AI from the perspective of industrial innovations (6) and innovative technologies (4). It also emphasizes associated issues related to the digital divide (4) and consumer protection (4). Additionally, this cluster underscores opportunities for state intervention and the importance of policies to regulate AI deployment, with keywords such as "state policy in the field of consumer protection" (4).

Cluster 5 centers on researching AI and cooperation utilizing a systemic perspective. The themes emphasized include self-adaptive systems (5), multi-agent systems (5), and the Internet of Things (IoT) (3).

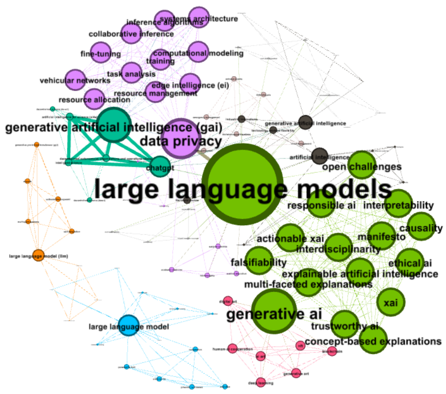

Fig. 4. Cooperation network

Coordination. Coordination is the least represented concept within this analysis, with the associated network comprising a total of 86 keywords joined by 230 links. The degree centrality of most keywords in this network is relatively low, resulting in a scattered discussion.

Cluster 1 emphasizes the integration of AI with advanced communication systems and autonomous coordination, particularly in the contexts of vehicular networks and robotics. Keywords such as "5G and B5G systems" (5), "V2V communication" (5), and "humanoid robots" (4) underscore the technical innovations driving real-time data exchange and coordination among autonomous agents. This cluster also emphasizes data management, with keywords like "information query" (4), "information retrieval" (4), "concept post-coordination" (3), and "edge-cloud networks" (3), alongside some connections to environmental sustainability, such as "green workload coordination" (3).

Cluster 2 focuses on a miscellaneous set of topics, including how generative AI can be leveraged for knowledge work, education, and facilitating human-machine communication. This is highlighted by keywords such as "conversational AI" (5), "knowledge work" (5), "cybernetics" (5), "education" (5), and "human-machine communication" (5). Additionally, there is a focus on the coordination and self-adaptation of multi-agent systems, with keywords like "MAPE-K (Monitor, Analyze, Plan, Execute, and Knowledge)" (5), "multi-agent systems" (5), and "self-adaptation" (5).

Cluster 3 stands out with its emphasis on generative AI models like ChatGPT (12) and their role in optimizing work coordination (12). Some attention is also given to the concepts of collective intelligence (7) and information governance (4) activities.

Cluster 4, although small, focuses on the practical applications of AI in software development, highlighting the integration of AI-driven tools within Integrated Development Environments (IDEs). Keywords such as "software development" (13), "IDE" (8), and "method renaming" (8) underscore this perspective.

Finally, Cluster 5 emphasizes the integration of AI in automotive engineering, particularly in enhancing human-machine collaborative decision-making and behavioral planning. Keywords such as "automotive engineering" (6), "behavioral planning" (6), and "human-machine collaborative decision-making" (6) may highlight the focus on developing AI systems that can interact effectively with human drivers to improve safety and efficiency in driving.

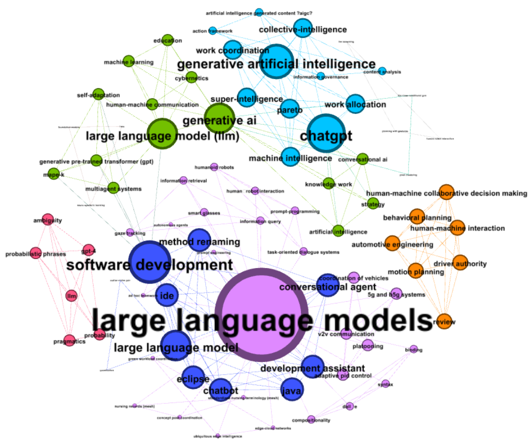

Fig. 5. Coordination network

4.3 Cross-dimension analysis

The Venn diagram (Fig. 6) reveals the distribution and overlap of papers containing one or a combination of the words "cooperation," "collaboration," "communication," and "coordination" in their title, abstract, or keywords. The low number of instances where multiple domains intersect within the same paper indicates that research focusing on the intersection of these themes is relatively scarce. Accordingly, a research gap exists in integrated studies that comprehensively address multiple dimensions of collaboration.

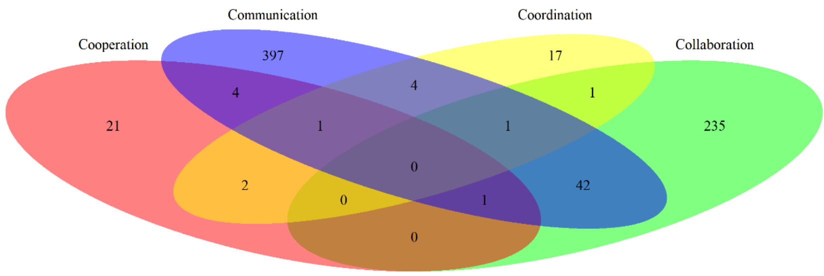

Fig. 6. Venn diagram: cross-dimension analysis

Specifically, a total of 21 instances mention only "cooperation," 235 instances mention only "collaboration," 397 instances mention only "communication," and 17 instances mention only "coordination." Apart from 42 instances where both "collaboration" and "communication" are mentioned, none of the domain combinations has been observed more than four times, and there are no instances where all four keywords are mentioned together.

These results point to a need for more holistic approaches in research on the implications of generative AI deployment in real work activities. They also highlight the imbalance in research focus that emerged in the historical analysis, showing that the dynamics of cooperation and coordination are largely under-emphasized.

5 Discussion and Conclusions

Generative AI is expected to profoundly impact work and organizational practices. Likely linked to its relatively emerging

Likely associated with the emerging nature of this technological innovation [34], existing research has predominantly analyzed the impact of Generative AI on individual tasks [see for instance 10–12], underplaying the collaborative and interdependent nature of work [19]. In line with this perspective, we argue that tasks within organizations are rarely isolated but are part of more complex, interdependent activities [18]. In these, humans are responsible not only for performing tasks but also for coordinating them by managing their interdependencies, cooperating, and communicating with others to achieve the desired outcome [18, 22].

Accordingly, this paper investigates the implications of generative AI on collaborative work activities, emphasizing the need to shift from a task-centric approach to a broader, process-oriented perspective. By utilizing the 3C collaboration model—communication, coordination, and cooperation—this study employs a bibliometric-based analysis to map the current state of research on this topic, identifying research gaps and opportunities for future studies.

First, our analysis reveals a significant disparity in academic focus on Generative AI and its implications on collaborative settings. In particular, while research on collaboration and communication has gained substantial attention (respectively accounting for 280 and 450 scientific contributions published), research on cooperation and especially coordination has been significantly under-emphasized (respectively, 29 and 26 contributions). This imbalance underscores a critical gap and presents an opportunity for further field development. Moreover, studies considering multiple collaboration dimensions are very limited, which we present as an additional avenue for future research.

Second, our analysis reveals that across all domains, there is strong attention to Human-AI interactions, especially in terms of collaboration. On the other hand, the role of generative AI as a mediator in Human-Human interactions is significantly less developed. This perspective is mainly present in the communication dimension, where generative AI can, for instance, improve the accessibility of technical information to non-experts, as seen in the medical domain with patient-physician interactions (cluster 1).

Third, we found thematic similarities among the research domains, notably a significant focus on educational and healthcare applications. Ethical considerations, such as responsible AI use and data privacy, are also recurrent themes, underscoring the importance of developing trustworthy AI systems. However, differences are notable in the specific applications and focus areas within each domain. For instance, collaboration research places a strong emphasis on creative and artistic activities, exploring AI's role in generative art and creative writing, which is less prominent in other domains. Communication research delves deeply into AI's transformative potential in personalized healthcare and secure data transmission, highlighting technological innovations like NLP and semantic communication. Coordination research has mainly focused on advanced communication systems and automotive engineering, with marginal attention given to work coordination. Keywords explicitly related to task interdependencies and collaborative workflows are not currently featured. Addressing this research gap could provide valuable insights into defining strategies to effectively integrate generative AI systems within complex organizational settings.

5.1 Theoretical implications

Our study has some theoretical implications. First, it emphasizes the necessity of integrating task-centric and process-oriented perspectives, recognizing these as different but complementary levels of analysis. This integration presents opportunities for integrating central theories in the field of Information Systems, such as coordination theory, to encompass both individual tasks and broader collaborative processes in AI-integrated work environments.

Our findings also suggest the potential for a more comprehensive theoretical model that incorporates all three collaboration dimensions (communication, coordination, and cooperation), providing a holistic understanding of AI's role in organizational dynamics. This should consider both the observed focus on Human-AI interactions, but also the relatively under-explored role of AI as a mediator in Human-Human interactions. Accordingly, this study calls for theoretical advancements in understanding both direct and indirect effects of AI on workplace interactions.

5.2 Practical implications

The practical implications of our study are far-reaching for organizations seeking to integrate generative AI into their collaborative work environments. Firstly, organizations should develop strategies that not only leverage AI's capabilities in individual tasks but also enhance overall workflow coordination and team cooperation. Secondly, the strong focus on Human-AI interactions in current research suggests that organizations should prioritize training programs that improve employees' ability to effectively collaborate with AI systems. Lastly, the under-explored area of AI as a mediator in Human-Human interactions presents an opportunity for developing innovative practices in using AI to enhance collaboration.

6 Limitations

This work has some limitations. First, while adopting a comprehensive lens to analyze collaboration and its associated dimensions, this study only considered four collaboration-related keywords within the data acquisition process. Future research will implement more detailed queries, including keywords related to teamwork and team dynamics. Second, this study utilized a single database for data acquisition. While Scopus is a widely utilized database, we aim to further develop this work by integrating data from other platforms (e.g., Web of Science). Third, although the keyword analysis provided a detailed and degree-centrality based thematic overview of the different dimensions explored in this study, some subjectivity in the interpretation may still exist. Future studies will enhance the robustness of the analysis by integrating a detailed systematic review of the identified bodies of literature, thereby increasing the depth of our analysis while reducing the potential for misinterpretation of the results.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Taecharungroj, V.: “What Can ChatGPT Do?” Analyzing Early Reactions to the Innovative AI Chatbot on Twitter. BDCC. 7, 35 (2023). https://doi.org/10.3390/bdcc7010035.
2. Giordano, V., Spada, I., Chiarello, F., Fantoni, G.: The impact of ChatGPT on human skills: A quantitative study on twitter data. Technological Forecasting and Social Change. 203, 123389 (2024). https://doi.org/10.1016/j.techfore.2024.123389.
3. Haque, M.U., Dharmadasa, I., Sworna, Z.T., Rajapakse, R.N., Ahmad, H.: “I think this is the most disruptive technology”: Exploring Sentiments of ChatGPT Early Adopters using Twitter Data. (2022). https://doi.org/10.48550/ARXIV.2212.05856.
4. Kalota, F.: A Primer on Generative Artificial Intelligence. Education Sciences. 14, 172 (2024). https://doi.org/10.3390/educsci14020172.
5. Nhavkar, V.K.: Impact of Generative AI on IT Professionals. IJRASET. 11, 15–18 (2023). https://doi.org/10.22214/ijraset.2023.54515.
6. Chui, M., Hazan, E., Roberts, R., Singla, A., Smaje, K., Sukharevsky, A., Yee, L., Zemmel, R.: The economic potential of generative AI: The next productivity frontier. McKinsey & Company (2023).
7. Eloundou, T., Manning, S., Mishkin, P., Rock, D.: GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models, http://arxiv.org/abs/2303.10130, (2023).
8. Brynjolfsson, E., Li, D., Raymond, L.: Generative AI at Work. National Bureau of Economic Research, Cambridge, MA (2023). https://doi.org/10.3386/w31161.
9. Milmo, D.: ChatGPT reaches 100 million users two months after launch, https://www.theguardian.com/technology/2023/feb/02/chatgpt-100-million-users-open-ai-fastest-growing-app, (2023).
10. Sudheesh, R., Mujahid, M., Rustam, F., Shafique, R., Chunduri, V., Villar, M.G., Ballester, J.B., Diez, I.D.L.T., Ashraf, I.: Analyzing Sentiments Regarding ChatGPT Using Novel BERT: A Machine Learning Approach. Information. 14, 474 (2023). https://doi.org/10.3390/info14090474.
11. Tufano, R., Mastropaolo, A., Pepe, F., Dabić, O., Di Penta, M., Bavota, G.: Unveiling ChatGPT’s Usage in Open Source Projects: A Mining-based Study, http://arxiv.org/abs/2402.16480, (2024).
12. Peng, S., Kalliamvakou, E., Cihon, P., Demirer, M.: The Impact of AI on Developer Productivity: Evidence from GitHub Copilot. (2023). https://doi.org/10.48550/ARXIV.2302.06590.
13. Kocoń, J., Cichecki, I., Kaszyca, O., Kochanek, M., Szydło, D., Baran, J., Bielaniewicz, J., Gruza, M., Janz, A., Kanclerz, K., Kocoń, A., Koptyra, B., Mieleszczenko-Kowszewicz, W., Miłkowski, P., Oleksy, M., Piasecki, M., Radliński, Ł., Wojtasik, K., Woźniak, S., Kazienko, P.: ChatGPT: Jack of all trades, master of none. Information Fusion. 99, 101861 (2023). https://doi.org/10.1016/j.inffus.2023.101861.
14. Noy, S., Zhang, W.: Experimental evidence on the productivity effects of generative artificial intelligence. Science. 381, 187–192 (2023). https://doi.org/10.1126/science.adh2586.
15. Lim, G., Perrault, S.T.: Rapid AIdeation: Generating Ideas With the Self and in Collaboration With Large Language Models. (2024). https://doi.org/10.48550/ARXIV.2403.12928.
16. Dell’Acqua, F., McFowland, E., Mollick, E.R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., Lakhani, K.R.: Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. SSRN Journal. (2023). https://doi.org/10.2139/ssrn.4573321.

17. Malone, T.W., Crowston, K.: What is Coordination Theory and How Can It Help Design Cooperative Work Systems. In: Proceedings of the Conference on Computer Supported Cooperative Work (1990).
18. Crowston, K., Rubleske, J., Howison, J.: Coordination Theory: A Ten-Year Retrospective. Human-Computer Interaction in Management Information Systems. (2004).
19. Ritala, P., Ruokonen, M., Ramaul, L.: Transforming boundaries: how does ChatGPT change knowledge work? JBS. 45, 214–220 (2024). https://doi.org/10.1108/JBS-05-2023-0094.
20. Arora, R., Goel, S.: Collaboration in software development: a spotlight. In: Proceedings of the CUBE International Information Technology Conference. pp. 391–396. ACM, Pune India (2012). https://doi.org/10.1145/2381716.2381789.
21. Fuks, H., Raposo, A., Gerosa, M.A., Pimentel, M., Filippo, D., Lucena, C.: Inter- and intra-relationships between communication coordination and cooperation in the scope of the 3C Collaboration Model. In: 2008 12th International Conference on Computer Supported Cooperative Work in Design. pp. 148–153. IEEE, Xian, China (2008). https://doi.org/10.1109/CSCWD.2008.4536971.
22. Fuks, H., Raposo, A., Gerosa, M.A., Pimental, M., Lucena, C.: The 3C Collaboration Model. The 3C Collaboration Model. 637–644 (2008).
23. Ellis, C.A., Gibbs, S.J., Rein, G.: Groupware: some issues and experiences. Commun. ACM. 34, 39–58 (1991). https://doi.org/10.1145/99977.99987.
24. Fuks, H., Raposo, A.B., Gerosa, M.A., Lucena, C.J.P.: APPLYING THE 3C MODEL TO GROUPWARE DEVELOPMENT. Int. J. Coop. Info. Syst. 14, 299–328 (2005). https://doi.org/10.1142/S0218843005001171.
25. Neto, J.D.S.C., Dornelas, J.S., Santos, A.G.: 7. Beyond the 3C Model in Collaboration Platforms: A Case Study. In: Machado, C. and Davim, J.P. (eds.) Innovation Management. pp. 135–148. DE GRUYTER (2015). https://doi.org/10.1515/9783110358759.135.
26. Fernandes, S., Barbosa, L.S.: Applying the 3C Model to FLOSS Communities. In: Yuizono, T., Ogata, H., Hoppe, U., and Vassileva, J. (eds.) Collaboration and Technology. pp. 139–150. Springer International Publishing, Cham (2016). https://doi.org/10.1007/978-3-319-44799-5_11.
27. Simona, T., Taupo, T., Antunes, P.: A Scoping Review on Agency Collaboration in Emergency Management Based on the 3C Model. Inf Syst Front. 25, 291–302 (2023). https://doi.org/10.1007/s10796-020-10099-0.
28. Brandenberger, J., Tylleskär, T., Sontag, K., Peterhans, B., Ritz, N.: A systematic literature review of reported challenges in health care delivery to migrants and refugees in high-income countries - the 3C model. BMC Public Health. 19, 755 (2019). https://doi.org/10.1186/s12889-019-7049-x.
29. Choi, I.: A Study on Effect of Trust, Relationship Commitment on Collaboration-Orientation (3C's), Performance and Satisfaction - Focused on Communication, Cooperation and Coordination. Journal of Marketing and HR. 4, (2017).
30. Laurillau, Y., Nigay, L.: Clover architecture for groupware. In: Proceedings of the 2002 ACM conference on Computer supported cooperative work. pp. 236–245. ACM, New Orleans Louisiana USA (2002). https://doi.org/10.1145/587078.587112.
31. Gerosa, M.A., Pimentel, M., Fuks, H., De Lucena, C.J.P.: Development of Groupware Based on the 3C Collaboration Model and Component Technology. In: Dimitriadis, Y.A., Zigurs, I., and Gómez-Sánchez, E. (eds.) Groupware: Design, Implementation, and Use. pp. 302–309. Springer Berlin Heidelberg, Berlin, Heidelberg (2006). https://doi.org/10.1007/11853862_24.
32. Lucas, E., Schneider, D., Oliveira, T., De Souza, J.: Investigating the collaborative support in CollabRDL: An analysis based on the 3C model. In: Proceedings of the 2014 IEEE 18th

International Conference on Computer Supported Cooperative Work in Design (CSCWD). pp. 529–534. IEEE, Hsinchu, Taiwan (2014). https://doi.org/10.1109/CSCWD.2014.6846900.

33. Medeiros, D., Ribeiro, E., Dam, P., Pinheiro, R., Motta, T., Loaiza, M., Raposo, A.B.: A Case Study on the Implementation of the 3C Collaboration Model in Virtual Environments. In: 2012 14th Symposium on Virtual and Augmented Reality. pp. 147–154. IEEE, Rio de Janiero, Brazil (2012). https://doi.org/10.1109/SVR.2012.28.
34. Rogers, E.M.: Diffusion of innovations. Free Press ; Collier Macmillan, New York : London (1983).
35. Abrahamson, E., Rosenkopf, L.: Social Network Effects on the Extent of Innovation Diffusion: A Computer Simulation. Organization Science. 8, 289–309 (1997). https://doi.org/10.1287/orsc.8.3.289.
36. Aula, P., Parviainen, O.: Communicating Connections: Social Networks and Innovation Diffusion. In: Melkas, H. and Harmaakorpi, V. (eds.) Practice-Based Innovation: Insights, Applications and Policy Implications. pp. 49–63. Springer Berlin Heidelberg, Berlin, Heidelberg (2012). https://doi.org/10.1007/978-3-642-21723-4_4.
37. Burt, R.S.: Social Contagion and Innovation: Cohesion versus Structural Equivalence. American Journal of Sociology. 92, 1287–1335 (1987). https://doi.org/10.1086/228667.
38. Strang, D., Soule, S.A.: Diffusion in Organizations and Social Movements: From Hybrid Corn to Poison Pills. Annu. Rev. Sociol. 24, 265–290 (1998). https://doi.org/10.1146/annurev.soc.24.1.265.
39. Beni Houd, Y., El Amrani, M.: Social Network Analysis: A useful tool for studying Innovation diffusion processes. Economia agro-alimentare. 1–59 (2022). https://doi.org/10.3280/ecag2022oa12059.
40. Haythornthwaite, C.: Social network analysis: An approach and technique for the study of information exchange. Library & Information Science Research. 18, 323–342 (1996). https://doi.org/10.1016/S0740-8188(96)90003-1.
41. Valente, T.W.: Social network thresholds in the diffusion of innovations. Social Networks. 18, 69–89 (1996). https://doi.org/10.1016/0378-8733(95)00256-1.
42. Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., Lim, W.M.: How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research. 133, 285–296 (2021). https://doi.org/10.1016/j.jbusres.2021.04.070.
43. Ahmadvand, A., Kavanagh, D., Clark, M., Drennan, J., Nissen, L.: Trends and Visibility of “Digital Health” as a Keyword in Articles by JMIR Publications in the New Millennium: Bibliographic-Bibliometric Analysis. J Med Internet Res. 21, e10477 (2019). https://doi.org/10.2196/10477.
44. Al-Khoury, A., Hussein, S.A., Abdulwhab, M., Aljuboori, Z.M., Haddad, H., Ali, M.A., Abed, I.A., Flayyih, H.H.: Intellectual Capital History and Trends: A Bibliometric Analysis Using Scopus Database. Sustainability. 14, 11615 (2022). https://doi.org/10.3390/su141811615.
45. Martínez-López, F.J., Merigó, J.M., Valenzuela-Fernández, L., Nicolás, C.: Fifty years of the *European Journal of Marketing* : a bibliometric analysis. EJM. 52, 439–468 (2018). https://doi.org/10.1108/EJM-11-2017-0853.
46. Blondel, V.D., Guillaume, J.-L., Lambiotte, R., Lefebvre, E.: Fast unfolding of communities in large networks. J. Stat. Mech. 2008, P10008 (2008). https://doi.org/10.1088/1742-5468/2008/10/P10008.
47. Freeman, L.C.: Centrality in social networks conceptual clarification. Social Networks. 1, 215–239 (1978). https://doi.org/10.1016/0378-8733(78)90021-7.