Towards Human-AI Collaborative Networks in Industry

Luis M. CAMARINHA-MATOS
School of Science and Technology, Centre of Technology and Systems (CTS) and LASI,
NOVA University Lisbon, Campus Caparica, 2829-156 Monte Caparica, Portugal
cam@uninova.pt

Abstract: The ongoing industrial transformation, as reflected in Industry 5.0, is increasingly driven by the rapid adoption of artificial intelligence (AI) and the growing hyperconnectivity of socio-technical systems, which highlights the importance of collaborative networks. Furthermore, AI is shifting from a tool-oriented perspective towards the notion of AI as a teammate, while the collaborative networks are evolving into hybrid human–AI collaborative networks. This paper explores the convergence of these two trends, identifying key research directions, some gaps, and open challenges. It further presents illustrative case studies from industrial contexts. It, thus, aims to contribute to a deeper understanding of the emerging hybrid collaborative networks in industry and of the need for adopting a multidisciplinary approach.

Keywords: AI teammate, Cobot, Collaborative business ecosystem, Hybrid human-AI collaborative network.

1. Introduction

The rapid and widespread adoption of artificial intelligence (AI) across nearly all economic sectors is transforming how organizations operate, innovate, and compete. In industrial contexts, AI applications have expanded from traditional automation and data analytics to advanced capabilities such as predictive maintenance, intelligent decision support, and adaptive process optimization (Zhang, Wang & Gao, 2025). This surge in AI-driven solutions reflects a broader technological shift that is reshaping the foundations of modern industry (Metakides & Filip, 2025).

This evolution aligns with the vision of Industry 5.0, which emphasizes advanced intelligent systems alongside human-centricity, resilience, and sustainability. Unlike the previous paradigms focused primarily on automation and efficiency, Industry 5.0 reintroduces the human element into industrial processes, positioning humans and intelligent systems as complementary actors (Yan et al., 2025). However, most current applications still treat AI mainly as a tool supporting human operators, rather than as an active participant in collaboration.

In parallel, the increasing hyperconnectivity of socio-technical systems has positioned collaborative networks as a key pillar of digital transformation (Camarinha-Matos et al., 2019). The modern industrial ecosystems are no longer composed of isolated organizations but of dynamic, interconnected networks enabling a flexible collaboration across enterprises and stakeholders.

More recently, a shift from tool-based AI toward AI as a teammate is emerging. Under this perspective, AI systems will increasingly participate in collaborative activities alongside humans, giving rise to hybrid collaborative networks where humans and AI agents jointly contribute to decision-making, coordination, and execution.

The convergence of human–AI collaboration and collaborative network paradigms is therefore becoming increasingly important (Camarinha-Matos, 2026). While these areas have largely evolved separately, their integration offers new opportunities to enhance flexibility, scalability, and performance in industrial ecosystems. However, the practical implementations remain limited in comparison with expectations, and in some cases they have fallen short (Challapally et al., 2025). Thus, understanding how AI teammates can be effectively designed and embedded in collaborative networks is a key challenge for next-generation industrial systems.

This paper addresses this emerging intersection by summarizing the current trends in human–AI collaborative networks in industry. It highlights the key research directions and presents representative cases illustrating the transition from human- and organization-centered networks to hybrid systems in which AI agents act as active collaborators. Through this synthesis, the paper contributes to a conceptual foundation for advancing the hybrid collaborative networks in industrial contexts.

The remainder of this paper is structured as follows. Section 2 highlights the converging

https://doi.org/10.24846/v35i2y202601

developments related to Artificial Intelligence and Collaborative Networks. Section 3 summarizes the current trends in human-AI collaborative networks in industry, while Section 4 provides a set of illustrative cases. Finally, Section 5 presents the conclusion of this paper.

2. Converging Developments

In recent years, a noticeable evolution can be observed in both Artificial Intelligence (AI) and Collaborative Networks (CNs), with increasing signs of convergence between the two areas. Although these fields originated from distinct research traditions and communities, their trajectories are progressively converging, particularly in the context of intelligent and distributed socio-technical systems.

AI, as one of the oldest research areas in computer science, has evolved over more than seven decades, with foundational work in symbolic reasoning, search, planning, and knowledge representation. After periods of slower progress, this field experienced a major resurgence driven by advances in machine learning, especially deep learning, as well as breakthroughs in natural language processing. More recently, the emergence of generative AI and agentic AI has further accelerated this evolution. The notion of collaborative agentic AI, in which multiple AI agents coordinate and interact with humans and other systems, becoming AI teammates, brings AI developments closer to the core concerns of Collaborative Networks.

In parallel, the evolution of CNs, a more recent field with a history of three to four decades, can be observed through a number of generations (Camarinha-Matos, 2026). Early developments (CNs 1.0) focused on single goal-oriented networks, such as extended enterprises, virtual enterprises and virtual organizations, aimed at achieving specific collaborative goals. The second generation (CNs 2.0) introduced long-term strategic networks acting as breeding environments for the rapid formation of dynamic virtual organizations; collaborative business ecosystems represent a key example for this stage. The third generation (CNs 3.0) addressed more complex scenarios involving the interplay of multiple networks, increasingly blurred organizational boundaries, and concepts such as co-creation and distributed value generation. With CNs 4.0, the scope expanded to include hybrid cyber-physical networks, where intelligent machines and systems participate as autonomous actors, shifting the systems development paradigm from control-oriented to collaboration-oriented perspectives. Finally, the emerging CNs 5.0 stage emphasizes hybrid human–AI collaboration, where artificial agents and humans jointly participate in networked problem solving and value creation processes.

As illustrated in Figure 1, these parallel evolutions reveal a clear convergence trajectory. The increasing autonomy, intelligence, and social capabilities of AI systems align naturally with the principles of collaborative networks, leading to a conceptual meeting point centred on AI teammates and hybrid human–AI collaborative networks. This convergence signals a transition toward more integrated, adaptive, and distributed systems, where collaboration is no longer limited to human or organizational actors but it extends to intelligent artificial entities as active participants.

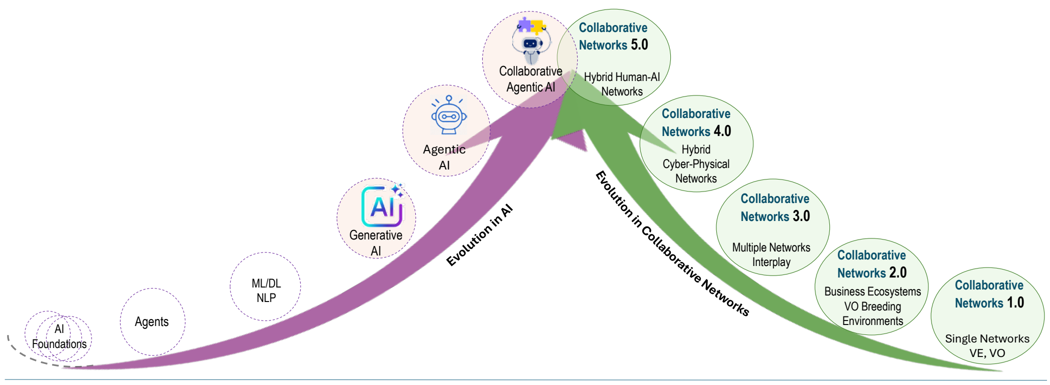

Figure 1. Convergence of AI and Collaborative Networks developments

In this context, two main notions have emerged:

- *Hybrid human-AI collaborative network*: a socio-technical system in which humans and AI agents work together to achieve shared goals, leveraging their complementary capabilities. In such networks, humans typically contribute with creativity, judgement, and domain expertise, while AI agents excel in large-scale data processing, pattern recognition, and optimization.

- *AI teammate*: an AI system (agent) designed to collaborate with humans and possibly other AI systems as an active partner (collaborator), rather than as a passive tool.

In industrial contexts, such teammates may take the form of software agents or embodied agents such as collaborative robots (cobots) or intelligent machines (Seeber et al., 2020). They are typically characterized by being collaborative, context-aware, adaptive and able to learn, proactive (they take initiative), and often having social capabilities so as to facilitate human-AI teamwork.

3. Recent Trends

Despite the recent hype surrounding AI, often accompanied by exaggerated expectations, the industrial landscape is still predominantly characterized by using AI as a tool, particularly through a growing number of machine learning applications. The genuine instances of AI functioning as a teammate in industrial contexts remain at an early stage of development.

In fact, this observation is also reflected in the research literature. A search in the SCOPUS database using the query *"industry" AND ("AI teammate" OR "human–AI collaboration" OR "collaborative robot" OR "hybrid network")* over the last five years indicates that most related publications focus on collaborative robotics. These works predominantly address lower-level concerns, such as ensuring the safe coexistence of humans and robots within shared workspaces and are largely centered on dyadic interactions involving a single human and a single robot. In contrast, the studies addressing human–AI teams represent only a small fraction of the literature (less than 10%). Nevertheless, some relevant trends can be identified as follows.

3.1 Collaborative Robots (Cobots)

Cobots are an extensively studied topic in the literature; however, despite the use of the term "collaborative," the focus has largely remained on low-level control aspects, while the more advanced collaborative capabilities are still mostly at the prototype or conceptual stage, as reflected in the following recurrent issues:

• *Classification*. Various cobot classes or forms of human–robot interaction are commonly identified in the literature (Othman & Yang, 2023; Patil, Vasu & Srinadh, 2023; Zafar, Langås, Sanfilippo, 2024), including: (i) *coexistence*, where humans and robots perform different tasks in separate workspaces without physical barriers; (ii) *sequential* or *synchronized collaboration*, where they share the same workspace but act at different times, requiring coordination; (iii) *cooperation*, where both operate simultaneously, possibly in overlapping spaces, without interfering, contributing to a shared goal; (iv) (responsible) *collaboration*, where they work together in the same workspace and timespan towards a common task (e.g. joint assembly); and (v) *human–robot teaming*, involving multiple humans and robots (and possibly other AI agents) pursuing a common goal. These forms are in contrast with traditional industrial robotics (fenced/caged systems), where humans and robots are physically separated. Most of them correspond to dyadic interactions (one human–one robot). In practice, the last form (human–robot teaming) would represent a true collaborative network, but remains largely immature, being mainly an aspiration. Some possible exceptions include robotic football and other cases in non-industrial applications.

• *Safety*. Safety remains a fundamental requirement, as humans and robots share a workspace without physical barriers. However, most efforts address a safe coexistence rather than a higher-level collaboration. A substantial amount of research focuses on motion planning, collision avoidance, detection, and mitigation (Gualtieri et al., 2024; Li et al., 2024), supported by sensing technologies, simulation, and standards such as ISO/TS 15066 (Asif et al., 2026).

• *Task / role allocation, balancing, and scheduling*. Task allocation consists in assigning tasks and decision authority based on capabilities and context, while roles define the interaction patterns (e.g. supervisor, peer) (Othman & Yang, 2023; (Yuan et al., 2025). Contributions include conceptual models and scheduling approaches (Casalino et al., 2021), skill alignment (Asif et al., 2026), assembly line balancing (Nourmohammadi, Fathi & Ng, 2022) and operator wellbeing (Calzavara, 2024). However, links to collaborative network methods remain limited, suggesting opportunities for applying multi-criteria partner selection approaches in more complex hybrid teams.

• *Teaching / learning collaborative behaviors*. Various works have explored how robots learn collaborative behaviors from human demonstrations, especially in assembly tasks (Zhang, Wang & Gao, 2021). Multimodal technologies, such as computer vision, natural language, and virtual/augmented reality, support these processes (Pérez et al., 2020). The more advanced approaches aim to predict human intentions (e.g. object handovers), a key capability still largely at the prototype stage (Wang et al., 2022). Other works also address broader teamwork design challenges, including interaction, roles, ergonomics, and flexibility (Kaasinen et al., 2022).

• *Programming & interaction.* Various approaches explore the use of augmented reality and mixed reality technologies for cobot programming (Yang, Xiao & Zhang, 2024; Costa, Petry & Moreira, 2022; Gallala et al., 2022). More recently, research has focused on leveraging large language models (LLMs) so as to enable more advanced forms of human–robot interaction (Wang, Fan & Zheng, 2024; Wu et al., 2026). These approaches are often complemented by multimodal capabilities, such as computer vision, for instance, for hand gesture recognition, and voice interaction, to create more intuitive and flexible programming interfaces (Mukherjee et al., 2022).

• *Ergonomics and layout design*. Ergonomic aspects, including the physical, cognitive, and social, are increasingly being considered in workspace design (Gualtieri et al., 2024; Chu, Pan & Chen, 2025). Approaches include workload-aware task allocation, layout optimization, human-centered design guidelines (Merlo et al., 2023) and minimization of mental stress (Proia et al., 2022). Virtual and augmented reality support simulation and participatory design.

• *Digital twins / technology integration*. Enabling technologies such as digital twins, mixed reality, and blockchain supports collaborative robotics deployment (Pérez et al., 2020). AI-enhanced, no-code platforms are also emerging (Shah, Doss & Lakshmaiya, 2025). Nevertheless, high-level collaborative capabilities (e.g. coordination, shared decision-making) remain limited.

• *Deployment and productivity analysis*. Various studies are increasingly addressing productivity and deployment decisions (Hashemi-Petroodi et al., 2020), including holistic evaluation models integrating economic and ecological aspects (Dornelles, Ayala & Frank, 2023). Challenges such as standardization, ethics, and resistance to change are also highlighted (Zafar, Langås, Sanfilippo, 2024).

3.2 General AI Teammates

Although still more limited in comparison with the extensive body of work on cobots, an increasing number of studies are emerging on the development and application of general AI teammates in industrial settings. Collectively, these works address a range of issues that reflect the current trends:

• *Towards hybrid networks*. A few studies are beginning to explore team structures involving multiple humans and multiple AI teammates (e.g. Narayanan & Feigh, 2026, Bansal et al., 2021 and Flathmann et al., 2023). Nevertheless, the majority of existing work remains focused on dyadic collaboration (i.e. one human interacting with one AI teammate).

• *Human-AI collaboration theories*. This topic encompasses the efforts to develop or adapt theoretical frameworks that support the understanding of interactions and behaviors within hybrid teams. Examples include models addressing shared mental model formation (Zhang & Chen, 2026), team situational awareness (Schelble et al., 2022), the input–mediator–output framework (O'Neill et al., 2023), and the emerging perspectives on the co-evolution of humans and AI (Sun et al., 2024).

• *Roles.* A substantial body of work focuses on characterizing the roles within hybrid teams and examining how role composition influences behavior and performance (Siemon, 2022). Other studies try to derive principles from human-only teams and adapt them to hybrid team settings (McNeese et al., 2021; O'Neill et al. 2023).

- *Interaction forms.* As in cobot research, various studies examined the interaction and communication modalities, along with the enabling technologies. A prominent stream focuses on the application and fine-tuning of large language models (LLMs) (Wu et al., 2025; Sun et al., 2024). Other relevant topics include agent transparency, AI explainability, and situation awareness, which are critical for an effective human-AI collaboration (Hauptman et al., 2024; Endsley, 2023; Vössing et al., 2022).

- *Trust and ethics*. Trust has long been a key issue in collaborative networks. In the context of human-AI collaboration, trust is often linked to AI explainability and agent performance (Hauptma et al., 2024; Hai et al., 2025; Endsley, 2023). It is also closely related to the extent to which ethical principles are embedded in the design of AI teammates (Textor et al., 2022). These aspects have additionally been explored in electronic commerce (Li et al. 2024), particularly in relation to the customer acceptance of chatbots.

- *Performance*. Various studies investigated the performance of hybrid teams and how factors such as role allocation, team composition, and situation awareness influence the outcomes (Bansal et al., 2021; Flathmann et al., 2023; Zhang & Chen, 2026).

- *Human aspects*. Another stream of research examines human-related factors such as expectations, sentiments, acceptance, and social perceptions of AI teammates, as well as the risks of work alienation and unethical behavior (Zhang et al., 2021; Hai et al., 2025; Harris-Watson et al., 2023). Other research works examine the effects on workforce skills, including deskilling and upskilling (Dornelles, Ayala & Frank, 2023), and the broader transformations enabled by Industry 4.0 technologies under concepts such as "smart working" (Dornelles, Ayala & Frank, 2022).

- *Symbiosis.* Some studies (e.g. Yan et al., 2025) explore how advanced collaboration models may enable a bidirectional cognitive evolution, in which humans and AI symbiotically co-evolve.

3.3 Who Designs the AI Teammates

Recent research is increasingly proposing design principles for AI teammates, including roles, constraints, and expectations, and also regarding the composition and management of hybrid teams. Many of these studies draw on social science perspectives or are conducted by social scientists (Gupta et al., 2025; Zhang, McNeese, Freeman, & Musick, 2021; Hauptman et al., 2024). While this interdisciplinary approach is enriching the field, it can also create tensions with the more traditional AI-oriented perspectives. Furthermore, some contributions from the social sciences are constrained by their grounding in the current state of technology, often not fully accounting for the anticipated evolution of AI capabilities. As the understanding of AI's capabilities and limitations is evolving and as technology advances, cross-disciplinary collaboration becomes essential for designing effective AI teammates and hybrid collaborative networks. The ethical considerations remain central, including human oversight, prevention of misuse (e.g. disinformation), trust and transparency, and the embedding of human values.

4. Examples

In line with these trends, illustrative examples of the evolution toward hybrid human–AI collaborative networks can be found in the work of the Collaborative Networks group at the Center of Technology and Systems (CTS), of NOVA University Lisbon. Over the past decades, the group has contributed extensively to Collaborative Networks research across multiple domains. Its models and frameworks are now being extended to incorporate AI teammates, enabling new forms of hybrid collaboration. Some representative examples are outlined below.

4.1 Industrial Collaborative Business Ecosystems

A Collaborative Business Ecosystem (CBE) is a long-term strategic network that enhances the preparedness of its member enterprises for collaboration, thereby enabling the rapid formation of dynamic virtual organizations in response to the emerging business opportunities (Graça & Camarinha-Matos, 2026). The key responsibilities of the CBE manager include assessing the ecosystem's performance and promoting a sustainable collaboration over time (Figure 2).

The overall behavior of the ecosystem is influenced by the characteristics of its members, such as their propensity to initiate collaborative opportunities, the readiness to engage in joint activities, and the openness to innovation-driven initiatives (membership profiles).

Furthermore, enterprises can be assumed to respond to evaluation mechanisms in ways which are similar to the ways how individuals respond. Their collaborative behavior can thus be influenced by adjusting the relative weights of the performance indicators. By tuning these weights, the CBE manager can actively guide and shape the evolution of the ecosystem. An AI agent can support the manager by enabling the exploration of alternative scenarios and assisting in decision-making.

In the current simulation platform, member enterprises are modeled as agents whose behavior is represented by using system dynamics. In future developments, these simulated agents may be replaced by enterprise digital twins, transforming the platform into a comprehensive collaborative management cockpit.

4.2 Collaborative Energy Ecosystems

The concept of a Collaborative Energy Ecosystem (CEE) integrates principles from Renewable Energy Communities, Virtual Power Plants, and Collaborative Networks (Adu-Kankam, Camarinha-Matos, 2023).

When the households within such a community are represented by Cognitive Digital Twins (DTs), conceived as AI agents endowed with a certain level of delegated autonomy from their human owners, the CEE can be seen as a hybrid human–AI collaborative network (Figure 3).

This delegation of autonomy enables DTs to actively participate in dynamic consortium formation for energy management purposes, for example in coordinating the sale of surplus energy to the grid. At the same time, human participants retain control over the degree of autonomy granted, preserving the ability to make critical decisions and override automated actions when necessary.

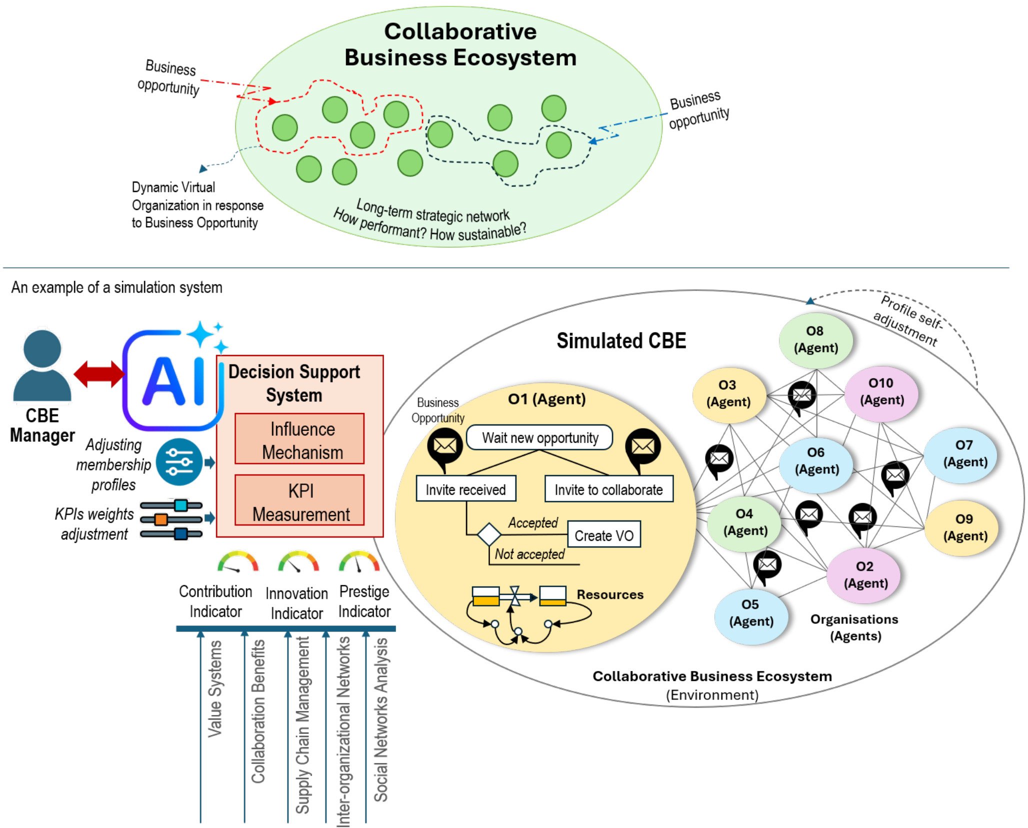

Figure 2. Example related to industrial Collaborative Business Ecosystems

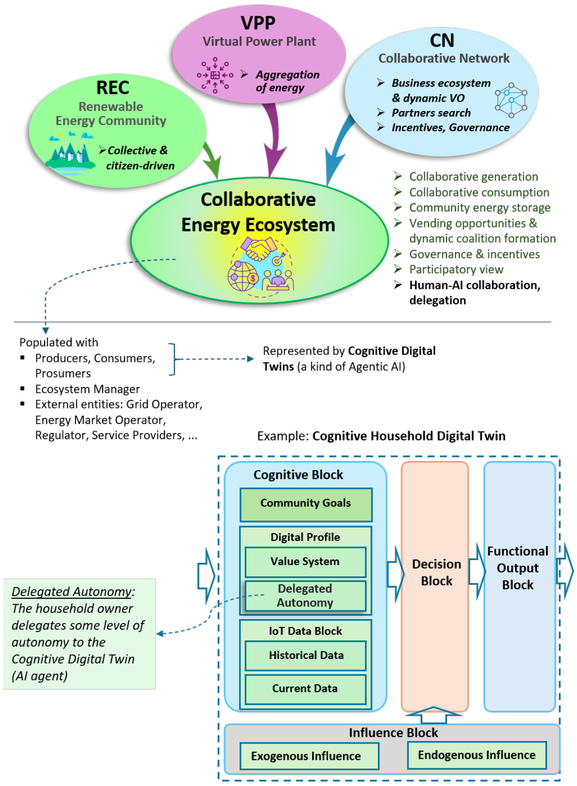

Figure 3. Example in Energy Management

4.3 Collaborative Cyber-Physical Systems Design

Designing a complex system such as a Collaborative CPS can benefit from intense human-AI collaboration. Figure 4 illustrates generic steps of such a co-design framework (Nazarenko & Camarinha-Matos, 2024).

In Step 1 (requirements elicitation), a LLM-based agent extracts requirements from plain-text descriptions of user needs. Human designers support this process by adding annotations to improve the extraction accuracy and by reviewing the results to identify and mitigate potential *hallucinations* or inconsistencies. Step 2 focuses on the selection of services that meet the identified requirements, as well as on the allocation of devices and sensors that enable these services. This process relies on service and device catalogues, as well as ontologies. A Discovery & Matching Agent assists human designers by ranking the candidate solutions and highlighting the potential conflicts. Designers validate these suggestions and contribute to defining the service logic and the associated rules.

In Step 3, high-level collaborative services are decomposed into more granular (capillary) services. Given that a CPS environment typically consists of a hierarchy of interconnected smart environments (e.g. different zones within a shop floor), the services and devices are allocated accordingly. The digital twins of devices and sensors then engage in a negotiation protocol to form coalitions capable of delivering the required collaborative services.

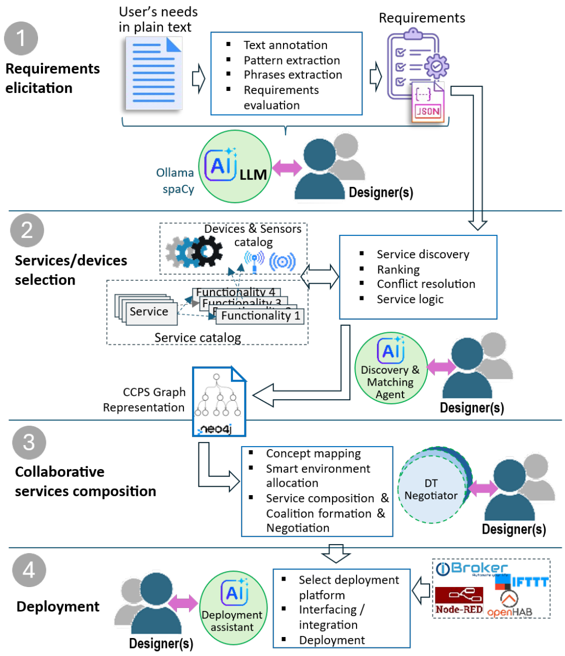

Figure 4. Collaborative Cyber-Physical Systems Design

The final deployment step involves selecting an appropriate platform (e.g. an IoT platform) and generating recommendations for runtime deployment, representing another key opportunity for AI assistance. Human designers remain essential for addressing integration and interoperability challenges, implementing the required protocols, and refining the service logic.

4.4 Elderly Care Ecosystem

Within the elderly care ecosystem, a variety of formal and informal service providers can collaboratively deliver integrated care services tailored to the specific needs of each elderly person (Baldissera, De Faveri, Camarinha-Matos, 2026) (Figure 5). Human–AI agent collaboration can support the planning phase by enabling the selection of appropriate services and providers, thereby facilitating the design of integrated care solutions that address the needs of the elderly (Example a).

Another scenario arises during daily activities, where AI agents and/or embodied AI (e.g.

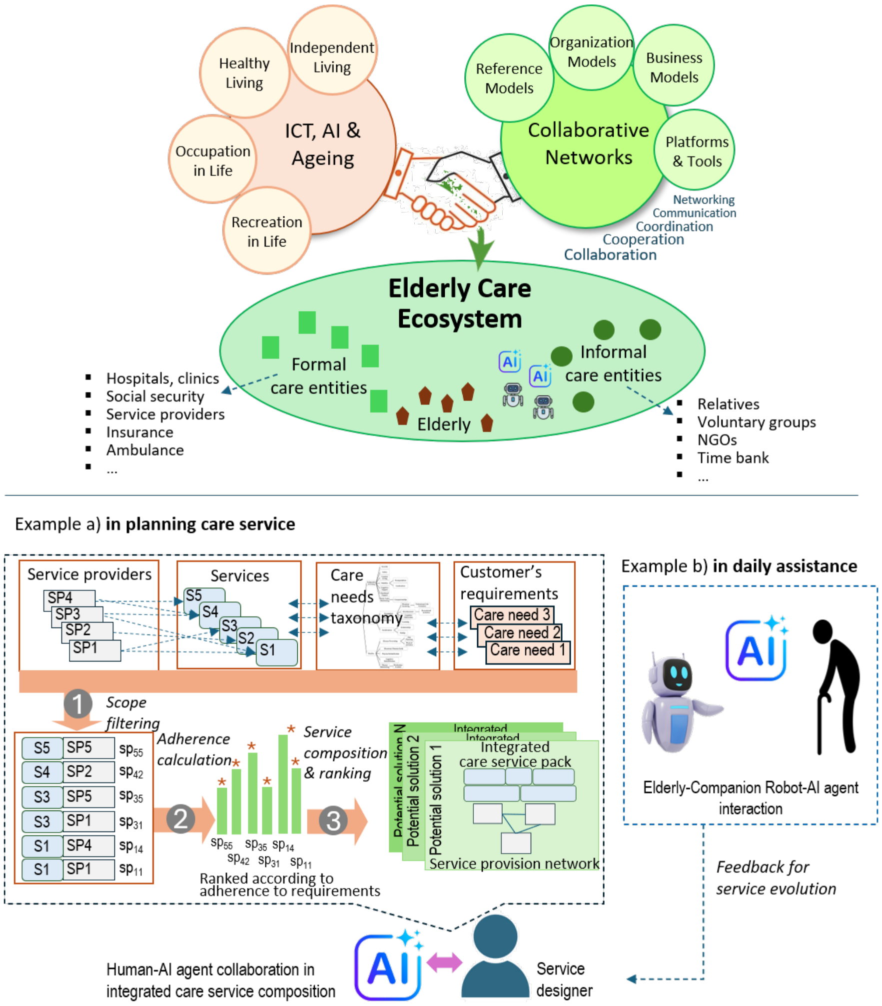

Figure 5. Example in Elderly Care Ecosystems

assistive / companion robots) support the elderly by monitoring the environmental conditions, interacting with individuals, and coordinating with service providers (Example b). Finally, the feedback generated from daily assistance can be incorporated into the planning process, enabling the continuous adaptation and improvement of services as the needs of the elderly evolve.

These examples illustrate how the developments in collaborative networks can be realistically extended through the inclusion of AI teammates.

5. Conclusion

This paper has examined the convergence of AI and collaborative networks in industrial contexts, leading to the emerging paradigm of hybrid human–AI collaborative networks. While AI has largely been deployed as a tool, the shift toward AI as a teammate marks a fundamental transition. However, the current implementations remain limited, with most research being still focused on the dyadic human–robot collaboration rather than fully networked multi-agent teamwork. The key challenges include enabling genuine collaborative intelligence, embedding the ethical principles such as transparency and human oversight, and developing design methodologies that integrate technical and social science perspectives. The illustrative cases presented demonstrate feasible pathways toward a hybrid collaboration. Achieving the full potential of Industry 5.0 will require multidisciplinary efforts to move from tool-based AI toward AI teammates operating within dynamic, human-centered collaborative networks.

Acknowledgements

This research was funded in part by Fundação para a Ciência e Tecnologia (Center of Technology and Systems – CTS), grant number UID/00066/2025.

REFERENCES

Adu-Kankam, K. O. & Camarinha-Matos, L. M. (2023) Modeling Collaborative Behaviors in Energy Ecosystems. *Computers*, 12(2), Art. no. 39. https://doi.org/10.3390/computers12020039.

Asif, S., Callari, T. C., Khan, F. et al. (2026) Exploring tasks and challenges in human-robot collaborative systems: A review. *Robotics and Computer-Integrated Manufacturing*. 97, Art. no. 103102. https://doi.org/10.1016/j.rcim.2025.103102.

Baldissera, T.A., De Faveri, C. & Camarinha-Matos, L.M. (2026). Generative Responsiveness in Assistive Care Ecosystem - GRACE. In: Camarinha-Matos, L.M., Ortiz, A., Boucher, X. & Lucas Soares, A. (eds.) *Hybrid Human-AI Collaborative Networks* (*26th IFIP WG 5.5 SOCOLNET Working Conference on Virtual Enterprises, PRO-VE 2025, 27-29 October 27-29 2025, Porto, Portugal, Part I*). vol. 770. Cham, Switzerland, Springer, pp. 413-427. https://doi.org/10.1007/978-3-032-05673-3_25.

Bansal, G., Nushi, B., Kamar, E. et al. (2021) Is the Most Accurate AI the Best Teammate? Optimizing AI for Teamwork. *Proceedings of the AAAI Conference on Artificial Intelligence*. *35*(13), 11405-11414. https://doi.org/10.1609/aaai.v35i13.17359.

Calzavara, M., Faccio, M., Granata, I. et al. (2024) Achieving productivity and operator well-being: a dynamic task allocation strategy for collaborative assembly systems in Industry 5.0. *International Journal of Advanced Manufacturing Technology*. 134(7-8), 3201–3216. https://doi.org/10.1007/s00170-024-14302-3.

Camarinha-Matos, L. M., Fornasiero, R., Ramezani, J. et al. (2019) Collaborative Networks: A Pillar of Digital Transformation. *Applied Sciences*, 9(24), Art. no. 5431. https://doi.org/10.3390/app9245431.

Camarinha-Matos, L. M. (2026). Collaborative Networks in Industry 4.0 and Industry 5.0, *Engineering*. https://doi.org/10.1016/j.eng.2026.01.009.

Casalino, A., Zanchettin, A. M., Piroddi, L. et al. (2021) Optimal Scheduling of Human–Robot Collaborative Assembly Operations with Time Petri Nets, *IEEE Transactions on Automation Science and Engineering*. 18(1), 70-84. https://doi.org/10.1109/TASE.2019.2932150.

Challapally, A., Pease, C., Raskar, R. et al. (2025) *State of AI in Business 2025: The GenAI Divide*. MIT. https://mlq.ai/media/quarterly_decks/v0.1_State_of_AI_in_Business_2025_Report.pdf. [Accessed 15th April 2026].

Chu C.-H, Pan J.-K. & Chen Y.-W. (2025) Ergonomic workplace design based on real-time integration between virtual and augmented realities, *Robotics and Computer-Integrated Manufacturing*. 92, Art. no. 102859. https://doi.org/10.1016/j.rcim.2024.102859.

Costa, G. d. M., Petry, M. R. & Moreira, A. P. (2022) Augmented Reality for Human–Robot Collaboration and Cooperation in Industrial Applications: A Systematic Literature Review. *Sensors*. 22(7), Art. no. 2725. https://doi.org/10.3390/s22072725.

Dornelles, J. de A., Ayala, N. F. & Frank, A. G. (2022) Smart Working in Industry 4.0: How digital technologies enhance manufacturing workers' activities, *Computers & Industrial Engineering*. 163, Art. no. 107804. https://doi.org/10.1016/j.cie.2021.107804.

Dornelles, J. de A., Ayala, N. F. & Frank, A. G. (2023) Collaborative or substitutive robots? Effects on workers' skills in manufacturing activities. *International Journal of Production Research*. 61(22), 7922–7955. https://doi.org/10.1080/00207543.2023.2240912.

Endsley, M. R. (2023) Supporting Human-AI Teams: Transparency, explainability, and situation awareness, *Computers in Human Behavior*. 140, Art. no. 107574. https://doi.org/10.1016/j.chb.2022.107574.

Flathmann, C., Schelble, B. G., Rosopa, P. J. et al. (2023) Examining the impact of varying levels of AI teammate influence on human-AI teams, *International Journal of Human-Computer Studies*. 177, Art. no. 103061. https://doi.org/10.1016/j.ijhcs.2023.103061.

Graça, P. & Camarinha-Matos, L.M. (2026) Hybrid Human-AI Performance Evaluation System for Collaborative Business Ecosystems. In: *Hybrid Human-AI Collaborative Networks* (*26th IFIP WG 5.5 SOCOLNET Working Conference on Virtual Enterprises, PRO-VE 2025, 27-29 October 27-29 2025, Porto, Portugal, Part I*). vol. 770. Cham, Switzerland, Springer, pp. 3-18. https://doi.org/10.1007/978-3-031-63851-0_1.

Gualtieri, L., Fraboni, F., Brendel, H. et al. (2024) Updating design guidelines for cognitive ergonomics in human-centred collaborative robotics applications: An expert survey, *Applied Ergonomics*, 117, Art. no. 104246. https://doi.org/10.1016/j.apergo.2024.104246.

Gupta, P., Nguyen, T. N., Gonzalez, C. et al. (2025) Fostering collective intelligence in human–AI collaboration: laying the groundwork for COHUMAIN, *Topics in Cognitive Science*. 17(2), 189-216, https://doi.org/10.1111/tops.12679.

Hai, S., Long, T., Honora, A. et al. (2025) The dark side of employee-generative AI collaboration in the workplace: An investigation on work alienation and employee expediency, *International Journal of*

Information Management. 83, Art. no. 102905. https://doi.org/10.1016/j.ijinfomgt.2025.102905.

Harris-Watson, A. M., Larson, L. E., Lauharatanahirun, N. et al. (2023) Social perception in Human-AI teams: Warmth and competence predict receptivity to AI teammates, *Computers in Human Behavior*. 145, Art. no. 107765. https://doi.org/10.1016/j.chb.2023.107765.

Hashemi-Petroodi, S. E., Thevenin, S., Kovalev, S. et al. (2020) Operations management issues in design and control of hybrid human-robot collaborative manufacturing systems: a survey, *Annual Reviews in Control*. 49, 264-276. https://doi.org/10.1016/j.arcontrol.2020.04.009 .

Hauptman, A.I., Schelble, B.G., Duan, W. et al. (2024) Understanding the influence of AI autonomy on AI explainability levels in human-AI teams using a mixed methods approach. *Cognition, Technology & Work.* 26, 435–455. https://doi.org/10.1007/s10111-024-00765-7.

Kaasinen, E., Anttila, A.-H., Heikkilä, P. et al. (2022) Smooth and Resilient Human–Machine Teamwork as an Industry 5.0 Design Challenge. *Sustainability*. *14(5)*, Art. no. 2773. https://doi.org/10.3390/su14052773.

Li, W., Hu, Y., Zhou, Y. et al. (2024) Safe human–robot collaboration for industrial settings: a survey. *Journal of Intelligent Manufacturing.* 35, 2235–2261. https://doi.org/10.1007/s10845-023-02159-4.

Li, Y., Li, Y., Chen, Q. et al. (2024) Humans as teammates: The signal of human–AI teaming enhances consumer acceptance of chatbots, *International Journal of Information Management*. 76, Art. no. 102771. https://doi.org/10.1016/j.ijinfomgt.2024.102771.

McNeese, N. J., Schelble, B. G., Canonico, L. B. et al. (2021) Who/What Is My Teammate? Team Composition Considerations in Human–AI Teaming. *IEEE Transactions on Human-Machine Systems*. 51(4), 288-299. https://doi.org/10.1109/THMS.2021.3086018.

Merlo E., Lamon E., Fusaro F. et al. (2023) An ergonomic role allocation framework for dynamic human–robot collaborative tasks. *Journal of Manufacturing Systems*. 67, 111-121. https://doi.org/10.1016/j.jmsy.2022.12.011.

Metakides, G. & Filip, F.G. (2025) Digital Enlightenment, Digital Humanism, and Computer-supported Collaboration in Artificial Intelligence Era, *Annals of Data. Science.* 12, 1799–1823. https://doi.org/10.1007/s40745-025-00640-w.

Mukherjee, D., Gupta, K., Chang, L. H. et al. (2022) A Survey of Robot Learning Strategies for Human -Robot Collaboration in Industrial Settings, *Robotics and Computer-Integrated Manufacturing*. 73, Art. no. 102231. https://doi.org/10.1016/j.rcim.2021.102231.

Narayanan, R. & Feigh, K. M. (2026) Designing for Oversight: An Empirical Investigation of the Dual Impact of AI Dependency and Information Abstraction on Human Supervision in Decision-Making Teams, *International Journal of Human–Computer Interaction*. 1-30. https://doi.org/10.1080/10447318.2026.2618568.

Nazarenko, A.A. & Camarinha-Matos, L.M. (2024) A Human-AI Framework to Design Collaborative Cyber Physical Systems. In: Camarinha-Matos, L.M. & Ferrada, F. (eds.) *Technological Innovation for Human-Centric Systems* (*15th IFIP WG 5.5/SOCOLNET Advanced Doctoral Conference on Computing, Electrical and Industrial Systems, DoCEIS 2024, 3-5 July 2024, Caparica, Portugal*). Vol. 716. Cham, Switzerland, Springer, pp. 28-42. https://doi.org/10.1007/978-3-031-63851-0_2.

Nourmohammadi, A., Fathi, M. & Ng, A. H. C. (2022) Balancing and scheduling assembly lines with human-robot collaboration tasks, *Computers & Operations Research*. 140, Art. no. 105674. https://doi.org/10.1016/j.cor.2021.105674.

O'Neill, T. A., Flathmann, C., McNeese, N. J. et al. (2023) Human-autonomy Teaming: Need for a guiding team-based framework?, *Computers in Human Behavior*. 146, Art. no. 107762. https://doi.org/10.1016/j.chb.2023.107762.

Othman, U. & Yang, E. (2023) Human–Robot Collaborations in Smart Manufacturing Environments: Review and Outlook. *Sensors*. *23*(12), Art. no. 5663. https://doi.org/10.3390/s23125663.

Patil, S., Vasu, V. & Srinadh, K.V.S. (2023) Advances and perspectives in collaborative robotics: a review of key technologies and emerging trends. *Discover Mechanical Engineering* 2, Art. no. 13. https://doi.org/10.1007/s44245-023-00021-8.

Pérez, L., Rodríguez-Jiménez, S., Rodríguez, N. et al. (2020) Digital Twin and Virtual Reality Based Methodology for Multi-Robot Manufacturing Cell Commissioning. *Applied Sciences*, *10*, Art. no. 3633. https://doi.org/10.3390/app10103633.

Proia, S., Carli, R., Cavone, G. et al. (2022) Control Techniques for Safe, Ergonomic, and Efficient Human-Robot Collaboration in the Digital Industry: A Survey. *IEEE Transactions on Automation Science and Engineering*. 19(3), 1798-1819. https://doi.org/10.1109/TASE.2021.3131011.

Schelble, B. G., Flathmann, C., McNeese, N. J. et al. (2022) Let's Think Together! Assessing Shared Mental Models, Performance, and Trust in Human-Agent Teams. *Proceedings of the ACM on Human-Computer Interaction*. 6, Issue GROUP, Art no. 13. https://doi.org/10.1145/3492832.

Seeber, I.; Bittner, E.; Briggs, R. O. et al. (2020) Machines as teammates: A research agenda on AI in team collaboration. *Information & Management*. 57(2), Art. No. 103174. https://doi.org/10.1016/j.im.2019.103174.

Shah, R., Doss, A. S. A. & Lakshmaiya, N. (2025) Advancements in AI-enhanced collaborative robotics: towards safer, smarter, and human-centric industrial automation, *Results in Engineering*. 27, Art. no. 105704. https://doi.org/10.1016/j.rineng.2025.105704.

Siemon, D. (2022) Elaborating Team Roles for Artificial Intelligence-based Teammates in Human-AI Collaboration. *Group Decision and Negotiation.* 31, 871–912. https://doi.org/10.1007/s10726-022-09792-z .

Sun, Y., Jang, E., Ma, F. et al. (2024) Generative AI in the Wild: Prospects, Challenges, and Strategies. In: *CHI '24: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, *11-16 May 2024, Honolulu, USA*. New York, USA, Association for Computing Machinery. Art. no. 747. https://doi.org/10.1145/3613904.36421.

Textor, C., Zhang, R., Lopez, J. et al. (2022) Exploring the Relationship Between Ethics and Trust in Human–Artificial Intelligence Teaming: A Mixed Methods Approach. *Journal of Cognitive Engineering and Decision Making*. 16(4). https://doi.org/10.1177/15553434221113964.

Vössing, M., Kühl, N., Lind, M. et al. (2022) Designing Transparency for Effective Human-AI Collaboration. *Information Systems Frontiers.* 24, 877–895. https://doi.org/10.1007/s10796-022-10284-3.

Wang, T., Fan, J. & Zheng, P. (2024) An LLM-based vision and language cobot navigation approach for Human-centric Smart Manufacturing, *Journal of Manufacturing Systems*. 75, 299-305. https://doi.org/10.1016/j.jmsy.2024.04.020.

Wang, W., Li, R., Chen, Y. et al. (2022) Predicting Human Intentions in Human–Robot Hand-Over Tasks Through Multimodal Learning, *IEEE Transactions on Automation Science and Engineering*. 19(3), 2339-2353. https://doi.org/10.1109/TASE.2021.3074873.

Wu, X.-K., Chen, M., Li, W. et al. (2025) LLM Fine-Tuning: Concepts, Opportunities, and Challenges. *Big Data and Cognitive Computing*. *9*(4), Art. no. 87. https://doi.org/10.3390/bdcc9040087.

Wu, D., Zheng, P., Zhao, Q. et al. (2026) Empowering natural human–robot collaboration through multimodal language models and spatial intelligence: Pathways and perspectives, *Robotics and Computer-Integrated Manufacturing*. 97, Art. no. 103064. https://doi.org/10.1016/j.rcim.2025.103064.

Yan, J., Liu, Z., Leng, J. et al. (2025) Human-centric artificial intelligence towards Industry 5.0: retrospect and prospect, *Journal of Industrial Information Integration*. 47, Art. ID 100903. https://doi.org/10.1016/j.jii.2025.100903.

Yang, W., Xiao, Q. & Zhang, Y. (2024) HAR^{2}bot: a human-centered augmented reality robot programming method with the awareness of cognitive load. *Journal of Intelligent Manufacturing.* 35(5), 1985–2003. https://doi.org/10.1007/s10845-023-02096-2.

Yuan, G., Liu, X., Qiu, X. et al. (2025) Human-robot collaborative disassembly in Industry 5.0: A systematic literature review and future research agenda, *Journal of Manufacturing Systems*. 79, 199-216. https://doi.org/10.1016/j.jmsy.2025.01.009.

Zafar M.H., Langås E.F. & Sanfilippo F. (2024) Exploring the synergies between collaborative robotics, digital twins, augmentation, and industry 5.0 for smart manufacturing: A state-of-the-art review, *Robotics and Computer-Integrated Manufacturing*. 89, Art. no. 102769. https://doi.org/10.1016/j.rcim.2024.102769.

Zhang, J., Wang, P. & Gao, R. X. (2021) Hybrid machine learning for human action recognition and prediction in assembly, *Robotics and Computer-Integrated Manufacturing*. 72, Art. no. 102184. https://doi.org/10.1016/j.rcim.2021.102184.

Zhang, J., Wang, L. & Gao, R. X. (2025) Embodied AI: A Foundation for Intelligent and Autonomous Manufacturing. *Engineering*. https://doi.org/10.1016/j.eng.2025.12.026.

Zhang, R., McNeese, N. J., Freeman, G. et al. (2021) "An Ideal Human": Expectations of AI Teammates in Human-AI Teaming. *Proceedings of the ACM on Human-Computer Interaction*. 4(CSCW3), Art. No. 246. https://doi.org/10.1145/3432945.

Zhang, X. & Chen, N. (2026) The Role of Shared Mental Models in Driving Knowledge Complementarity: Enhancing Human–AI Team Effectiveness, *International Journal of Human–Computer Interaction*. https://doi.org/10.1080/10447318.2025.2598670.