

Mapping the Human-AI Collaboration Trends in Design Research: A Systematic Review

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Abstract. This systematic review provides an overview of the academic discourse on human-AI (HAI) collaboration within the design discipline. The selected papers were analysed through action coding, encapsulating the papers' approach—*designing, evaluating, discussing*, and structural coding, indicating the papers' core topics—*human creativity, training, specific tasks, collaborative environments, ethical concern, interaction, co-creation, communication, decision-making, trust, and team dynamics*. The papers are analysed and visualised in a network based on their assigned codes, revealing their relationships to one another. This interpretative effort contributes to knowledge by developing a bottom-up coding approach to identify key discourse clusters within the rapidly evolving literature on HAI collaboration, defining and discussing such clusters, and recognising relevant trends in the debate. The review highlights a current emphasis on practically driven studies over critical and reflective ones, suggesting the need for more integrated approaches that combine both perspectives.

Keywords: Human-AI collaboration, Human-AI interaction, Artificial intelligence, Design research, Design teams, Systematic review.

1 Introduction

The capacity of AI to process enormous amounts of data has led numerous working sectors to adopt it, triggering changes in their professional practices. In this transformative scenario, while there is a visionary goal of developing fully autonomous AI to replace human labour, there is also a growing interest in exploring how AI can collaborate effectively with humans [1, 2]. At the state of the art, humans and AI possess complementary skills and expertise that can be combined to accomplish tasks neither can achieve alone [3]. This opens new possibilities for managing the increasing complexity of our ever-evolving society, potentially enabling us to address contemporary societal challenges more effectively.

Human-AI (HAI) collaboration represents a novel and distinctive form of interaction unlike any we have encountered before. The characteristics and

challenges inherent in this collaboration are unique [4], differing not only from traditional human-human collaborations but also from those investigated within the field of human-computer interaction [5]. Indeed, AI is not only a computational algorithm but also a disruptive technology capable of altering social interactions within a team [6, 7]. Thus, AI potential also comes with challenges that – if not correctly addressed – can lead to volatile HAI interactions and oscillatory outcomes.

While still embryonic and lacking a shared definition, the domain of HAI collaboration is characterised by a rapidly increasing number of publications. Although this proliferation reflects the field's richness of perspectives, it also leads to fragmentation, making it difficult to trace coherent research trajectories [8, 9]. This is particularly evident when we refer to the HAI collaboration issue in the design discipline. AI integration into design practice has gained momentum more recently, as academics and practitioners increasingly investigate how to incorporate its capabilities into design workflows. The design field is captivated by the potential of incorporating AI and is contemplating the consequences of this integration. Mapping efforts [8] suggest that research on AI within the design discipline can be understood as distributed across several areas, including the design process, theoretical concerns, AI development, human-AI interaction, and AI-infused artefacts. While early contributions primarily framed AI as a support tool or as an object of ontological inquiry, more recent developments—driven by advances in machine learning and generative systems [10]—have expanded its role toward that of an active actor in design practice. In this context, AI is increasingly involved in tasks such as exploration, visualisation, generation, and evaluation, contributing to a shift from purely functional deployment toward more relational and collaborative forms of interaction [11].

To better understand these dynamics, scholars have developed a range of frameworks to articulate the mechanics of human-AI collaboration. Foundational work on mixed-initiative co-creativity [12] conceptualises collaboration as a dynamic process in which both human and computational agents contribute proactively to the creative trajectory. This perspective has been further elaborated through structural models that examine how initiative, control, and contribution are distributed between actors [13–15]. Together, these frameworks provide a more fine-grained understanding of interaction dynamics, highlighting the negotiated and evolving nature of human-AI partnerships.

Alongside these conceptual works, a growing body of research has examined the broader implications of integrating AI into design practice. These include changes in trust and transparency [16, 17] and emerging challenges related to decision-making, agency, and creative control [18, 19]. More broadly, scholars have begun to identify shifts in design workflows, in which designers increasingly interpret, filter, and evaluate AI-generated outputs [20, 21]. These changes are accompanied by affective and ethical concerns [22, 23], including issues of authorship, responsibility [24–26], and the broader societal and environmental impact of AI technologies [27].

Given the richness of these perspectives, the literature remains heterogeneous and only partially structured. Different research strands often develop in parallel,

with limited integration across conceptual frameworks, empirical studies, and design-oriented reflections. As a result, the discourse can appear fragmented, making it difficult to trace coherent research trajectories or to understand how different approaches relate to one another [9].

In light of the described scenario, this work aims to address the exploratory research question: “How are scholars addressing the HAI collaboration issue in design?” It contributes to the ongoing debate in three ways: by developing a bottom-up coding approach to normalise a divergent body of literature; by identifying emerging clusters; and by discussing relevant trends. As such, rather than offering an exhaustive account which may be difficult to achieve in a rapidly evolving field, this work provides an interpretative snapshot of the early development of HAI collaboration in design, aiming to support future research.

2 Methodology

2.1 Search Protocol

The Prisma model protocol [28] informed our review, providing a formal checklist to guide its conduction and reporting. The review focused on collecting relevant design studies regarding HAI collaboration and offering a general overview of the main discourse patterns. To this end, the search strategy was constructed to reflect the intersection of three core conceptual components: artificial intelligence, collaboration, and design. These components were operationalised through corresponding sets of keywords, combined to retrieve publications on HAI collaboration in design contexts. The search query¹ was intentionally designed to balance breadth and precision, capturing contributions from multiple disciplines while maintaining a focus on design-related applications.

The search was conducted in the Scopus database in 2023. Scopus was selected as a source due to its broad interdisciplinary coverage and the availability of structured metadata and filtering options, which are particularly suited to systematic reviews spanning multiple domains, including design, human-computer interaction, engineering, and the social sciences. We acknowledge that relying on a single database may have excluded relevant studies indexed in other venues. This trade-off was considered acceptable in light of the study’s aim to

1 TITLE-ABS-KEY ("artificial intelligence" OR "AI" OR "machine learning" OR "ML" OR "deep learning" OR "DL") AND TITLE-ABS-KEY ("human-ai" OR "collaboration" OR "team") AND ALL ("design process" OR "product design" OR "industrial design" OR "design team") AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "ch")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "SOCI") OR LIMIT-TO (SUBJAREA, "DECI") OR LIMIT-TO (SUBJAREA, "ARTS") OR LIMIT-TO (SUBJAREA, "PSYC") OR LIMIT-TO (SUBJAREA, "MULT"))

provide a structured and interpretable snapshot of the field rather than an exhaustive account, balancing breadth with analytical tractability.

In this sense, additional inclusion criteria were applied to refine the corpus and ensure its relevance to the research scope. The document types were limited to journal articles, conference proceedings, and book chapters, and only publications in English were considered. Furthermore, subject-area filters were used to retain records most likely to address HAI collaboration from a design-oriented and socio-technical perspective, namely Computer Science, Social Sciences, Decision Sciences, Arts and Humanities, Psychology, and Multidisciplinary. These filters were intended to reduce non-relevant results while preserving the interdisciplinary nature of the topic, resulting in an initial corpus of 568 papers.

As expected in a rapidly evolving field, rerunning the same query at a later stage (March 2026) yields a larger number of records (1258). However, to ensure methodological consistency, the present review is based on the dataset retrieved at the time of the original search.

The collected publications were shortlisted through three screening phases. First, an initial filtering step removed ineligible records, including duplicates, non-peer-reviewed publications (e.g., editorials or notes), and entries with incomplete bibliographic information. This was followed by an abstract screening and a full-text review, both aimed at assessing each paper's relevance to the intersection of human-AI collaboration and design.

The abstract screening excluded records clearly out of scope, while the full-text review ensured that the remaining studies meaningfully engaged with HAI collaboration within a design context. Papers were retained only if they explicitly addressed this intersection and excluded if AI or design was treated marginally or without a clear collaborative dimension. As a result, a substantial portion of the initially retrieved records was excluded, leading to a final corpus of 48 studies.

2.2 Corpus Analysis

After refining the corpus, we carefully reviewed each paper, identifying the main take on HAI collaboration for each. To achieve this, we employed action and structural coding [29]. Each paper was assigned an action code, representing the publication's primary objective, and a structural code, indicating its main topic. The combination of these two codes highlighted the paper's core contribution. Ultimately, we identified three action codes – *designing*, *evaluating*, and *discussing* – and eleven structural codes – *human creativity*, *training*, *specific tasks*, *collaborative environments*, *ethical concern*, *interaction*, *co-creation*, *communication*, *decision-making*, *trust*, and *team dynamics*.

This interpretative effort was driven by the explorative research question: how are scholars addressing the HAI collaboration issue in design? To answer such a question, we aimed to break down the complexity of HAI collaboration into smaller thematic clusters for more straightforward analysis and reflection. We contend that finding a method for normalising publications into comparable

elements aids in better understanding the trajectory of academic discourses and developing structured knowledge that facilitates more systematic discussions.

3 Results

This section describes the codes and presents each paper according to its assigned coding. As mentioned, every paper is categorised by action and structural codes. Regarding action coding, three codes emerge: *designing*, *evaluating*, and *discussing*.

- **Designing** refers to papers focused on driving practical change in the current state of HAI collaboration. These papers typically involve the creation of artefacts, applicable frameworks, or guidelines intended to be implemented to improve or transform HAI collaboration practices.
- **Evaluating** centres on assessing how HAI collaboration occurs across various contexts. These studies are primarily empirical, aiming to understand the dynamics and impacts of HAI collaboration rather than proposing immediate changes. Their goal is to provide insights into the phenomenon and its impact on real-world applications.
- **Discussing** encompasses theoretical papers that address HAI collaboration from a broad, speculative, and reflective perspective. These studies focus on conceptual exploration and discussion of the issues, offering theoretical frameworks, interpretations, and potential future directions without necessarily aiming for direct, practical application.

Hereafter, we present the structural codes in relation to the corresponding papers.

3.1 Collaborative Environments

The papers addressing this topic discuss the environment in which humans and AI collaborate (Table 1). The scope of these publications is to reflect on the space in which the collaborative dynamics occur, with the final aim of understanding how it affects the overall work experience.

Table 1. Publications included in the Collaborative Environments structural code.

Publication	Action Code	Structural Code
Zhang et al. (2022)	Designing	Collaborative Environments
Urban Davis et al. (2021)	Designing	Collaborative Environments
Koch et al. (2020)	Designing	Collaborative Environments
Song et al. (2020)	Discussing	Collaborative Environments

Designing—Collaborative Environments. The study by Zhang et al. [30] focused on developing a prototype platform that integrates multiple AI models, enabling designers to collaborate with them more efficiently. The central concept behind the platform is to build what the authors defined as a ‘melting pot’, an integrated design flow space in which designers can perform several tasks, such as creative stimulation and design evaluation, while engaging in self-reflective practices. Urban Davis et al. [31] presented a HAI creative collaboration interface for virtual reality. The interface is meant to help designers explore divergent solutions within a virtual environment through a collaborative dialogue with AI. Koch et al. [32] developed an AI-powered creative support platform to encourage convergent and divergent thinking. This collaborative environment aims to help multiple designers compose a shared mood board, provoking different levels of inspiration and reflection. The results showed that the platform helped designers with the project’s composition and traceability. In particular, designers found AI suitable for expanding their idea space because it could introduce new materials into the process. On the other hand, designers preferred collaborating with humans when they already knew what they were looking for.

Discussing—Collaborative Environments. Song et al. [33] reviewed the state-of-the-art of collaborative design research platforms, identifying four attributes that define a well-designed working environment for HAI collaboration: the capacity to support multiple design phases, support hybrid teams with AI, support various design scenarios, and support data-driven analyses

3.2 Team Dynamics

These studies focus on understanding the main consequences of introducing AI into human teams (Table 2). In particular, the aim is to investigate how the working and social interactions among team members change in hybrid HAI teams, and the impact on the quality of teamwork.

Table 2. Publications included in the Team Dynamics structural code.

Publication	Action Code	Structural Code
Zhang et al. (2021)	Evaluating	Team Dynamics
Song et al. (2022)	Evaluating	Team Dynamics
Kang (2007)	Evaluating	Team Dynamics
Schechter et al. (2023)	Evaluating	Team Dynamics
Viros-i-Martin and Selva et al. (2021)	Discussing	Team Dynamics

Evaluating—Team Dynamics. Zhang et al. [34] tried to assess the impact of a deep learning AI on the performance, behaviour, perceived workload, and confidence of humans in HAI teams. They observed in the study that AI can be a valid support to the initial performance of low-performing teams, but hinders the performance of high-performing teams. Building on the study of Zhang et al., Song

et al. [35] studied how evolving and abrupt changes affect the team's design process. The results showed significantly greater agility in HAI teams compared to human-only teams when dealing with abrupt changes in the design process. HAI teams demonstrated better interdisciplinary collaboration, resulting in improved adaptability. Additionally, HAI teams surpassed human-only teams in terms of quality of communication and a broader exploration of the design space. Kang [36] examined how AI's behaviour within a team, precisely its level of activeness and cooperativeness, influences team efficiency. The author described AI's activeness in two levels, active and passive, and AI's cooperativeness in three levels: cooperative, neutral, and selfish. Schecter et al. [37] proposed an experimental method to examine the collaborative dynamics between humans and AI through a video-conferencing application.

Discussing—Team Dynamics. Viros-i-Martin and Selva [38] presented a framework that describes the interactions between humans and AI occurring in the early phases of the design process. To do so, they treated both humans and AI as intelligent agents and aligned their attributes with prior literature on human cognition in design, human-machine collaboration, and design teams.

3.3 Co-Creation

In the following papers, humans and AI collaborate to produce tangible artefacts through a process of co-creation (Table 3). As the outcome of this joint effort, the resulting artefact requires contributions from both humans and AI, emphasising that it cannot be achieved solely through the input of either. As a result, researchers consider AI to be close to an ideation partner, meaning humans are no longer the only source of innovative and creative work [39, 40]. In a co-creation scenario, scholars seem to shift away from treating humans and AI as two completely distinct entities within a design team, opting for a comprehensive, interdependent system perspective in which both are considered proactive agents [24].

Table 3. Publications included in the Co-Creation structural code.

Publication	Action Code	Structural Code
Kantosalo and Toivonen (2016)	Designing	Co-Creation
Long et al. (2019)	Designing	Co-Creation
Wu et al. (2021)	Discussing	Co-Creation
Fu and Zhou (2020)	Discussing	Co-Creation

Designing—Co-Creation. Kantosalo and Toivonen [13] developed a framework for analysing and designing new co-creative HAI systems. They focused primarily on identifying different kinds of creative processes, such as symmetric alternating, asymmetric alternating, and task-divided co-creation. The first two defined two roles AI can take: pleasing or provoking the human. In the latter, they recognised

three possible roles playable by humans and AI: concept definer, concept generator, and concept evaluator. Long et al. [41] provide a set of design principles for developing co-creative AI systems for public interaction spaces. These principles aim to help others design AI that enhances public engagement, fosters collaboration, and promotes AI literacy in informal learning environments such as museums, galleries, and public installations.

Discussing—Co-Creation. Wu et al. [42] reflected on how HAI collaboration enhances creativity by leveraging the strengths of both humans and AI, stating that collaborating with AI will benefit humans far more than competing against it. They proposed the definition of “AI creativity”, intended as the humans’ ability to co-live and co-create with AI, and the “human-AI co-creation model”. In their vision, HAI collaboration is essential to boosting productivity, inspiring innovation, and empowering creativity. Fu and Zhou [43] argued that AI has the potential to positively influence human creativity through co-creation, but its role needs to be carefully tailored to different stages of the design process. They proposed the Human-AI Co-Creation model, which emphasises that AI should adapt its role as a tutor, facilitator, or partner based on the context to enhance human creativity without causing interference.

3.4 Interaction

Papers within this structural code focus on the practical interactions between humans and AI during HAI collaboration (Table 4). These studies aim to better explore how designers engage with AI at a more grounded, operational level.

Table 4. Publications included in the Interaction structural code.

Publication	Action Code	Structural Code
Amershi et al. (2019)	Designing	Interaction
Shergadwala and Seif El-Nasr (2021)	Designing	Interaction
Tsiakas and Murray-Rust (2021)	Designing	Interaction
Arzberger et al. (2022)	Evaluating	Interaction
Yang et al (2020)	Discussing	Interaction
Jiang et al (2022)	Discussing	Interaction
Lee et al. (2023)	Discussing	Interaction
Jang and Nam (2022)	Discussing	Interaction

Designing—Interaction. Amershi et al. [44] proposed 18 design guidelines to improve HAI interactions, particularly regarding the usability, trustworthiness, and effectiveness of AI-infused systems, which can help designers create more intuitive, predictable, and user-centric interactions. Similarly, Shergadwala and Seif El-Nasr [45] outlined several guidelines for designing AI to improve HAI interaction. To do so, they defined the AI design requirements through the specific

lens of human-centric design. Additionally, they identified challenges, such as bias and intellectual property, that need to be addressed when developing human-centric AI models. Tsiakas and Murray-Rust [46] integrated the concepts of 'explainable AI' and 'human-in-the-loop' to create new possibilities in HAI collaboration. By directly involving human users in AI learning and decision-making, these methods enable more personalised, fair, and reliable AI systems that can improve both individual and organisational performance in future work practices.

Evaluating—Interaction. Arzberger et al. [47] reflected on the use of HAI dialogue to enhance humans' understanding of design problems. The authors highlighted three distinctive AI capabilities present in HAI collaboration: the AI's ability to frame design problems, the AI's ability to create stories that can foster an emotional connection with the designer, and the AI's ability to play different roles for the designer (i.e., creative inspiration, critic, mediator). The authors showed how AI can aid divergent thinking by helping designers think of new problem dimensions and the consequences of possible solutions.

Discussing—Interaction. Yang et al. [48] investigated why HAI interactions are uniquely difficult for the design discipline, identifying two specific AI attributes as culprits: capacity uncertainty and output complexity. Building on this, they mapped the main challenges that design scholars and practitioners must face when integrating AI into their practice. Similarly, Jiang et al. [49] reflected on recurrent challenges and opportunities arising when humans and AI interact. Thus, they developed the 'Situation Awareness' theoretical framework, which addressed the tension between automation and human agency, system (i.e., AI) uncertainty and user confidence, and the system's (i.e., AI) objective complexity and users' perceived complexity. Lee et al. [50] reflected on a future where AI technologies interact with humans continuously, blending into their everyday lives. They envisioned different possibilities through high-fidelity illustrations, helping designers and users alike anticipate how AI may integrate into daily life. Similarly, Jang and Nam [51] adopted a speculative design approach to build five narratives about future issues in HAI collaboration. The narrative can help design scholars speculate on desirable states of HAI interactions in which humans and AI can communicate efficiently.

3.5 Communication

The following studies aim to improve the communication between humans and AI (Table 5). This is a recurrent topic when dealing with HAI interactions since state-of-the-art AI can be considered 'black boxes', making its work modalities obscure to humans and thus difficult to understand [52, 53]. Similar to human-only teams, communication is also an impactful factor in the social dynamics of HAI teams, influencing the team's working experience and, consequently, the final team outcome.

Table 5. Publications included in the Communication structural code.

Publication	Action Code	Structural Code
Jia et al. (2021)	Designing	Communication
Gyory et al. (2021)	Evaluating	Communication
Liao et al. (2020)	Discussing	Communication
Endsley (2023)	Discussing	Communication
Wulff and Finnestrand (2023)	Discussing	Communication

Designing—Communication. Jia et al. [54] proposed a visual, explainable active learning framework with four actions—ask, explain, recommend, and respond—to promote HAI teaming. The visualisation allows humans and AI to communicate in a shared space where inputs and outputs can be exchanged smoothly.

Evaluating—Communication. Gyory et al. [55] focused on how AI reshapes and potentially improves team communication when introduced into a human-only team. In particular, the authors observed higher quality and greater richness in discourse content.

Discussing—Communication. Liao et al. [17] explored the operational opportunities and challenges in adopting AI explainability techniques in design practice. Through their work, the authors mapped the attributes of AI that are essential to humans for better communication. Endsley [56] highlighted the importance of AI's transparency and explainability during HAI interactions, as they can create trust imbalances among team members, harming overall performance. Wulff and Finnestrand [57] argued that integrating Explainable AI into organisations should be approached holistically, considering both the AI's technical aspects and the organisational task structures. In their view, explainability challenges can be reduced through effective organisational design based on sociotechnical systems principles, thereby enhancing HAI collaboration and creating more productive work environments.

3.6 Trust

Similar to how trust affects the collaborative dynamics in human-human relationships, it also plays a crucial role in HAI collaboration (Table 6). Humans need to establish relationships with a proper balance of trust if they want the HAI collaboration to be successful. Otherwise, humans could trust AI too much (i.e., over-trust) or too little (i.e., under-trust), leading, in the first case, to misuse and, in the second, to disuse [16]. Thus, trust allocation and balance appear to be challenging factors when dealing with HAI collaboration.

Table 6. Publications included in the Trust structural code.

Publication	Action Code	Structural Code
Schmager and Sousa (2021)	Designing	Trust
Jain et al. (2022)	Designing	Trust
Chong et al. (2022)	Evaluating	Trust
Chong et al. (2022)	Evaluating	Trust
Chong et al. (2022)	Evaluating	Trust
Zhang et al. (2022)	Evaluating	Trust
Zhang et al. (2023)	Evaluating	Trust
Figoli et al. (2022)	Evaluating	Trust

Designing—Trust. Schmager and Sousa [58] developed a toolkit to design trustworthy AI. They identified a lack of available ethical guidelines that can obstruct practical HAI applications. Thus, they listed practical methods and tools to design AI that can convey designers' trust more easily. Jain et al. [59] developed a model for organisations wishing to integrate AI within their workflows. They emphasised the importance of considering employees' perceived aversion to AI when introducing it into the work environment. Organisations can minimise aversion towards AI by improving conditions, thereby enhancing its acceptance.

Evaluating—Trust. Chong et al. [60] investigated humans' confidence towards AI and themselves. They observed that the former directly influenced humans' perception of AI's ability to perform a given task, while the latter influenced their propensity to trust AI. In their opinion, good decision-makers display a positive correlation between confidence and self-confidence. However, they also highlighted a potential risk: a vicious cycle in which poor AI performance diminishes human self-confidence, increasing individual reliance on AI outcomes. The authors followed this work with subsequent studies [61, 62] that showed that AI's accuracy can correlate differently with designers' confidence in AI and their self-confidence. When AI is proficient, there is no clear association between the designer's confidence and their propensity to trust AI. Whereas, when AI performs poorly, designers tend to rely on AI only when they are not confident in themselves. Zhang et al. [63, 64] explored the effects of deceiving designers into believing they are working with human teammates rather than AI. Their results indicate that designers do not achieve better performance when deceived by AI's identity, suggesting no increase in the quality or quantity of HAI interactions. Figoli et al. [65] explored design students' perceived trust in AI when introduced early in the design process, particularly during the concept generation phase. The results showed that students' perceptions were highly susceptible, with most shifting substantially after engaging in hands-on AI experiences. In their view, training students in HAI collaboration is a valuable way to improve their awareness and judgmental skills.

3.7 Ethical Concerns

The breakthrough of AI models, now widely available to the masses, has sparked heated debates in mainstream media over their ethical implications. Data security, individual privacy, and artistic authorship are just a few of the emerging ethical issues. However, interestingly, of the 48 papers included in the review, only one explicitly focuses on ethical concerns arising from integrating AI into the design discipline (Table 7).

Table 7. Publications included in the Ethical Concerns structural code.

Publication	Action Code	Structural Code
Van der Waa et al. (2021)	Discussing	Ethical Concerns

Discussing—Ethical Concerns. The investigation by Van der Waa et al. [66] examines the implications of teaming humans and AI, particularly for morally salient tasks. The authors believe humans should exert meaningful control over the AI when moral decisions must be made. This control must align with generally accepted human moral values and accepted ethical guidelines.

3.8 Human Creativity

The following scholars' studies examine AI's capacity to empower human creativity (Table 8). Humans can utilise the material provided by AI to trigger lateral thinking, encouraging them to think outside the box [67]. For this reason, design phases that rely on idea generation and problem-solving, such as brief definition and concept generation, are particularly suited to HAI collaboration.

Table 8. Publications included in the Human Creativity structural code.

Publication	Action Code	Structural Code
Lin et al. (2020)	Designing	Human Creativity
Karimi et al. (2019)	Designing	Human Creativity
Kim et al. (2023)	Designing	Human Creativity

Designing—Human creativity. Lin et al. [68] focused on how robots, like their system "Cobbie", can foster ideation during conceptual design through sketching. The results showed the AI's capacity to enhance engagement and provoke unexpected ideas. Their study found that robots are more effective in encouraging exploration and creativity than virtual agents, demonstrating the potential of tangible, embodied AI systems in creative design processes. Another computational model aimed at encouraging design creativity through sketching was proposed by Karimi et al. [69]. Their model selects concepts with high, intermediate, or low visual-semantic similarity to the designer's sketch. High similarity helps designers combine two concepts; intermediate similarity helps

them adjust the range of values of the initial concept; and low similarity helps them add new features to the initial design. Similarly, Kim et al. [70] developed a sketching collaborative ideation partner that supports human idea generation in two dimensions: conceptual and visual similarity. The HAI collaboration is designed as a turn-taking interaction between humans and AI. The authors discovered that during ideation, conceptual similarity without visual similarity yields more ideas, while visual similarity without conceptual similarity yields higher-quality ideas.

3.9 Specific Tasks

Studies in this topic refer to AI situated at specific moments in the design process to accomplish specific design activities (Table 9). In this sense, the designer defines a specific setting for AI application, rendering it highly specialised in achieving the expected goal.

Table 9. Publications included in the Specific Tasks structural code.

Publication	Action Code	Structural Code
Krishnamurthy (2020)	Designing	Specific Tasks
Lee et al. (2022)	Designing	Specific Tasks
Zhang et al. (2017)	Designing	Specific Tasks

Designing—Specific tasks. Chen and Krishnamurthy [71] presented a digital mind-mapping workflow for generating ideas in collaboration with AI. The model can identify potential target nodes for idea addition and extract new insights from the node's relationship to enable mind map evolution. Lee et al. [72] used conversational transcripts to propose a method for developing mind maps similar to human-generated ones. Zhang et al. [73] built a framework for concept clustering during product development by applying an AI concept clustering tool. By comparing AI-generated clusters with human-generated ones, they highlighted patterns of over- and under-clustering that may improve the team's ability to build clusters and evaluate design concepts.

3.10 Decision-Making

The studies on decision-making examine AI's ability to influence the decision-making process through HAI collaboration (Table 10). The main aim of these AI applications is to improve the efficiency of the process leading to a decision and the accuracy of that decision.

Table 10. Publications included in the Decision-Making structural code.

Publication	Action Code	Structural Code
Gyory et al. (2022)	Designing	Decision-Making
Gyory et al. (2022)	Designing	Decision-Making
Bayrak et al. (2019)	Evaluating	Decision-Making
Bayrak et al. (2021)	Evaluating	Decision-Making
Bayrak et al. (2021)	Evaluating	Decision-Making

Designing—Decision-making. Gyory et al. [74] presented an AI process manager capable of guiding the design process of engineering teams in real time. Their work demonstrated the AI's efficiency in dynamically tracking insights from the teams' design process and converting them into appropriate interventions. The study results showed that the AI process manager matches the capabilities of human process managers, such as intervention efficacy. The authors further investigated the issue with an additional study [75] that highlighted a relationship between humans' responses and the type of intervention performed by the AI. For example, communication-focused interventions strongly influenced the team process, while others, such as design-action-focused interventions, had a reduced impact.

Evaluating—Decision-making. Bayrak et al. [76] reflected on a possible HAI collaboration dynamic in which humans and AI collaborate on strategic decisions, acting as peers in various problem-solving situations. The study's results showed the AI's ability to identify novel and opening strategies in the early stages of the design process. However, humans remain responsible for assessing the quality of the AI suggestion and, based on this, make the final decision. Hence, AI supports and enhances human decision-making ability. In subsequent studies [77, 78], the authors further investigated the issue, presenting new insights into the decision-making processes of hybrid HAI teams.

3.11 Training

In the following studies, the core goal is to offer valuable knowledge to improve the training of AI, both in terms of how to guide the training and how to achieve a better-trained AI (Table 11). Human data is collected and provided to the AI model to improve the dataset's quality, enabling it to "reason" more closely with humans.

Table 11. Publications included in the Training structural code.

Publication	Action Code	Structural Code
Raina et al. (2019)	Designing	Training
Kim and Lim (2021)	Designing	Training

Designing—Training. Raina et al. [79] extracted insights from human designers' problem-solving skills to develop an AI that could simulate them. In the authors'

view, if the design process can be considered a sequential decision-making process, AI can be trained to identify design patterns and strategies to generate designs comparable to human-generated ones. Kim and Lim [80] introduced the teaching-learning interaction framework, shifting the traditional AI-user relationship by empowering users to act as “teachers” to AI, guiding the learning process rather than passively receiving services.

4 Discussion

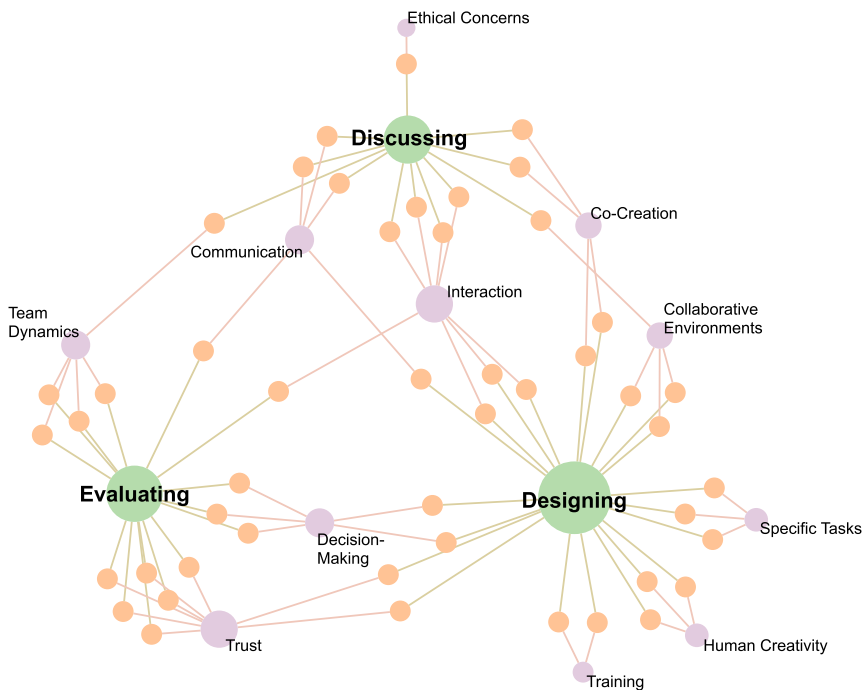


Fig. 1. The network visualises the entire corpus of papers (nodes without labels) in relation to the action (*designing, evaluating, discussing*) and structural codes (*team dynamics, trust decision-making, training, human creativity, specific tasks, collaborative environments, co-creation, ethical concerns, interaction, communication*).

4.1 Action Codes and Structural Codes

Figure 1 shows how the selected papers (nodes without labels), the action codes and the structural codes relate to each other. In particular, if structural codes identify the paper’s core topic, their distribution in the network highlights how scholars address it. Several considerations can be made. Three clusters emerge—*designing, evaluating, and discussing*—each composed of action code, structural

code and the linking papers. Additionally, a meta-cluster arises from the overlap of these three clusters, encompassing core topics that are present across different approaches. This meta-cluster, referred to as the *integrative cluster*, highlights the interconnectedness between concepts such as *communication*, *interaction*, *decision-making*, and *co-creation* (Fig. 2).

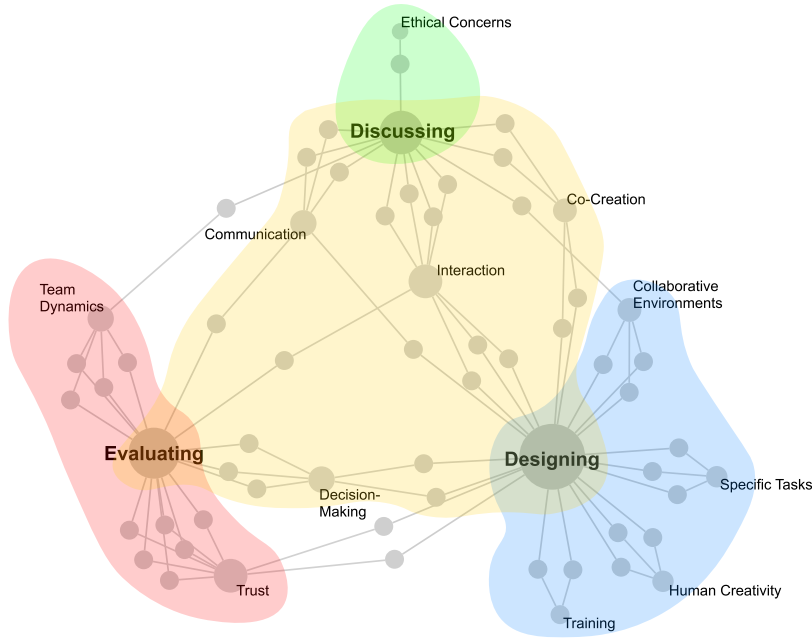


Figure 2 – The four clusters of the network: *designing* (blue), *evaluating* (red), *discussing* (green), and *integrative* (yellow).

The *designing cluster*, centred on the *designing* code, includes *training*, *human creativity*, *specific tasks*, and *collaborative environments*. The cluster shows that scholars study these topics primarily to bring practical change to HAI collaboration. Interestingly, compared to other structural codes, those within this cluster address defined and situated issues in HAI collaboration, such as the training of AI, the development of specialised AI capable of performing a specific task, and the definition of the space where the collaboration occurs. Although part of this cluster, human creativity stands out as a more abstract and broadly defined topic. The emphasis on *designing* in this context may stem from the inherent challenge of empirically evaluating creativity [81]. As a result, studies in this cluster often prioritise the creation and testing of designed artefacts.

The *evaluating cluster*, built on the *evaluating* code, encompasses *team dynamics* and *trust*. This cluster focuses on understanding how HAI collaboration unfolds in practice. Here, scholars aim to assess the potential impact on social dynamics caused by the introduction of AI in traditionally human-only processes. The social aspects of HAI collaboration are a key component of the phenomenon,

emphasising AI not only as a technological entity but also as a social one, capable of affecting the dynamics within collaborative settings [6, 82]. The focus on evaluation in these studies suggests that scholars are mainly concerned with measuring HAI collaboration's performance, reliability, and implications, helping to build a foundational understanding before more concrete changes can be designed or implemented.

The *discussing cluster*, centred on the *discussing* code, comprises ethical concerns. This cluster represents a theoretical and reflective approach in which scholars critically engage with HAI collaboration. In this context, scholars mainly reflect on "what AI is?" to better understand "what it should be?" The only paper in the cluster aims to address ethical issues within the HAI collaboration discourse, envisioning possible trajectories to ensure fair AI implementation in the future.

The *integrative cluster* includes structural codes that are significantly interconnected with more than one action code, positioning them at the heart of the network. These structural codes—*communication*, *decision-making*, *interaction*, and *co-creation*—hold a central place in the HAI collaboration discourse, discussed across both practical and theoretical approaches. In other words, scholars address these topics to drive practical changes, assess their dynamics, and critically analyse their implications. These topics are deeply interrelated, forming the backbone of any HAI collaboration. In every such setting, humans and AI must interact, communicate effectively, share decision-making processes, and engage in co-creation to achieve successful outcomes.

4.2 Trends in the HAI Collaboration Debate

The analysis and visualisation of the papers, through action and structural coding, help us highlight trends in HAI collaboration. Notably, this approach enables us to observe which action and structural codes are the most recurrent.

The four clusters presented in the previous section indicate the four trends of how scholars address the topics within the HAI discourse. Here, we explore the data more deeply, considering each code separately to uncover distinct trends.

Designing, Evaluating, Discussing. The majority of the corpus of papers falls under the action code of *designing*, followed by *evaluating* and *discussing*. This distribution suggests that the focus in HAI research leans toward practical applications, with scholars aiming to develop new frameworks, tools, and artefacts to improve HAI collaboration pragmatically. This observation points to a possible tendency for design scholars to engage with the HAI debate primarily through technological innovation and experimentation, with comparatively less emphasis on critical reasoning and theoretical reflection. This tendency is common in discussions around novel technologies, where initial attention often focuses on functionality before broader questions of meaning are considered [83].

A closer look at the relationship between action codes and structural codes further reinforces this interpretation. *Designing* is not only the most recurrent

approach but also the one connected to the widest range of topics (eight in total), with four of them—*collaborative environments*, *specific tasks*, *human creativity*, and *training*—being almost exclusively addressed through design-oriented contributions. In contrast, *evaluating* is associated with a more limited set of topics (five), with *trust* and *team dynamics* being the two topics almost exclusively addressed through this approach. *Discussing*, while present across four topics, appears primarily linked to *ethical concerns*, which in this corpus are addressed in only one contribution.

This distribution suggests the emergence of distinct research trajectories, in which specific topics tend to be approached by researchers through consistent modes of inquiry: *design*-driven work concentrates on the development of applications and contexts of use; *evaluation*-oriented studies focus on relational and performance-related aspects; and *discussion*-based contributions engage with broader implications.

From this perspective, fostering a more balanced distribution across action codes becomes relevant. This would entail engaging the same topics through *designing*, *evaluating*, and *discussing*, rather than predominantly through a single approach. Such a rebalancing could support more articulated research trajectories, in which practical development, empirical assessment, and critical reflection inform one another. Notably, the topics included in the integrative cluster already exhibit a more balanced distribution, suggesting a possible direction for future research.

4.2 Most Recurrent Topics

From Figure 1, it is possible to observe the main discourse patterns in HAI collaboration literature by counting the number of papers for each structural code. These aspects are particularly significant because they indicate where design scholars have focused their attention and energy. The most recurrent structural codes are listed below in order of the paper's quantity.

Trust. This topic is a crucial factor in HAI collaboration. Indeed, most collaborative dynamics between humans and AI involve iterative exchanges, with each party providing inputs and receiving outputs. In this process, both over-trusting and under-trusting can lead to dysfunctional HAI interactions, negatively impacting the humans' willingness to rely on AI suggestions and the quality of the collaboration task [16]. Therefore, humans are asked to establish HAI relationships with a proper balance of trust, leading to improved work and outcomes. Design scholars approach this issue in two distinct ways, depending on the study's focus. In the first approach, humans are the subject of the investigation, with the research objective centred on enhancing their ability to allocate trust in AI effectively. In the second approach, the subject shifts from humans to AI, with the investigations aimed at improving AI's trustworthiness, i.e., its ability to earn human trust. Interestingly, the first approach seeks to empower humans to become proficient evaluators who can judiciously trust AI, whereas the second

approach focuses on enhancing the attractiveness of AI. These two approaches could pose a challenge, as efforts to enhance AI's trustworthiness might inadvertently hinder humans' ability to allocate trust effectively, which is the primary objective of the first approach.

Interaction. Studies within this structural code focus on the practical and operational dynamics between humans and AI. Scholars are particularly interested in how these interactions can be optimised to foster more effective collaborations. The three action codes—*designing*, *evaluating*, *discussing*—reflect three approaches utilised by scholars when analysing *interaction*: offering practical guidance, understanding the phenomenon, and envisioning possible futures.

In the first case, scholars employ frameworks and guidelines for efficient collaboration and for designing AI systems to support effective interaction. In the second case, the interaction is explored to unpack the phenomenon's complexity as it currently unfolds in current working settings, identifying possible interaction modalities and the roles of both humans and AI. Finally, the third case takes a forward-looking perspective, with scholars using reflection and speculation to envision potential future scenarios for HAI collaboration, defining pathways for how these interactions might evolve.

Team Dynamics. These studies explore how introducing AI into human teams affects working and social interactions, focusing on how these changes influence teamwork quality. The proximity of the structural node to the *evaluating* action node reveals the most commonly employed approach: assessing the results of integrating AI into design teams. Within this core scope, scholars addressed the issue in two modalities: the first examines how humans respond to AI when it is introduced into their work setting, including changes in behaviour, perception, and performance. The second focuses on how AI behaves in such environments, examining its role as an entity with agency and how its behaviour—such as levels of activeness and cooperativeness—affects overall team efficiency and dynamics.

Communication. Like trust, communication is crucial to the input-output exchange between humans and AI during a collaborative task. The primary objective of studies in this topic is to transform AI from a 'black box' into a transparent entity [56]. This is achieved by providing descriptions and accessibility to its internal reasoning and behaviours. Interestingly, although communication in HAI collaboration could inherently involve human and AI competencies as crucial actors, the academic discourse primarily focuses on enhancing AI capabilities. This leaves the aspect of improving humans' ability to communicate with AI relatively underexplored. Consequently, communication in HAI collaboration is less about refining the quality of communication itself and more about bolstering AI's capacity to be more understandable to humans. This trend is also evident in how scholars dedicated to HAI communication have coined

terms such as ‘explainable AI’ and ‘AI transparency’ to define subfields within this field.

Decision-making. This topic refers to HAI collaboration studies aimed at understanding how AI influences the decision-making process of a HAI team and, eventually, at improving it. Scholars treat the issue through two main approaches: First, AI provides humans with new data and suggestions to enhance their decision-making capacity. Humans retain the right to choose and direct the project in accordance with their vision and understanding. In the second, the relationship is inverted. AI decides for humans, managing the process on a higher level, while humans are asked to follow it. Thereby, as also observed across other topics, tensions may emerge between these differing perspectives. Researchers tend to explore contrasting scenarios: one in which humans retain decision-making authority, and another in which AI assumes a leading role, potentially reconfiguring or even subverting the hierarchy between humans and AI.

4.3 Least Recurrent Topics

Given this work’s aim of providing an overview of the HAI collaboration discourse, it is essential to give equal attention to both the less frequently discussed studies and the more commonly explored ones. Based on the timeframe of the literature review, these less-addressed areas could be understood as thematic gaps in the academic design literature, warranting further exploration. Furthermore, considering why these subjects have received less attention in recent years than others could offer additional interpretations of the ongoing discussion.

Ethical Concerns. Only one publication presented ethics as its structural code, a noteworthy result that contrasts with the heated debates over ethics and AI prevalent in the mass media. Introducing AI into daily life has sparked numerous concerns about its alignment with commonly held ethical principles. AI trained on biased and non-inclusive datasets, the appropriation of personal data privacy, infringement upon copyrighted material, diminishment of human agency, authorship ambiguity, and the potential replacement of human jobs are just a few of the emerging ethical issues. As a field actively integrating AI, design should focus on these issues, as they have significant implications for professional practice. Ideally, design scholars and practitioners should concurrently develop both HAI practices and HAI ethics. This approach is preferable as it is easier to shape practices before they become firmly established. On the other hand, incorporating ethical issues into AI development could potentially lead to a significant slowdown in HAI research and implementation, which could be critical for design, a discipline that naturally evolves in tandem with rapidly changing society. This points to a potential misalignment in pace, where ethical reflection may develop more slowly than technological advancement, leading interventions to lag behind ongoing innovation.

Training. These investigations focus on improving the AI training process through collaboration with humans. In this view, humans act as trainers, while AI is positioned as the entity being trained. Incorporating human data into AI development remains a critical challenge, as it can contribute to making AI more aligned with human needs and contexts. However, this framing tends to stabilise roles that are, in practice, more fluid. Both humans and AI, particularly machine learning models, continue to adapt over time through ongoing interaction. From this perspective, HAI collaboration can be understood as a dynamic process in which both parties continuously adjust their behaviour with respect to the other. Engaging with training in this way would shift the focus from a unidirectional transfer of knowledge to a mutual and evolving adaptation, where roles are not fixed but emerge through use.

Current Practice. When interpreting these less frequently discussed topics, it is also important to consider their implications for current design practice, which does not explicitly emerge as a node in the corpus. At the time of the review (2023), AI was already being integrated across multiple phases of the design process, including problem framing, ideation, and prototyping—areas that are not directly reflected in the mapped topics. This suggests a misalignment between practice and academic literature, as they operate on inherently different temporalities: rapid implementation and iteration in practice, and slower cycles of analysis and publication in research. In a fast-evolving field such as HAI collaboration, this divergence becomes particularly relevant, as practice may continue to evolve, while academic research follows with a delay. As a result, the literature may capture only partial or already-shifting configurations of HAI collaboration.

From this perspective, methodological approaches that rely less on literature and are more directly grounded in practice—such as grounded theory [84]—may offer a way to address this limitation. Furthermore, rather than focusing primarily on specific tools or systems, which are subject to rapid obsolescence, future research could prioritise more stable analytical lenses, such as interaction patterns, forms of agency, and distributions of responsibility within human–AI collaboration.

5 Limitations and Future Works

This study presents some limitations that should be considered when interpreting the results, while also pointing to directions for future research.

First, the corpus is not intended to be exhaustive of the entire HAI collaboration literature. Although the selection process followed defined criteria, relevant contributions may have been excluded due to the use of a single database (i.e., Scopus) and the timing of the review (conducted in 2023), particularly given the rapid expansion of publications in this field. As a result, some topics, approaches, or emerging trends may not be fully captured. Future work could address this

limitation by expanding the corpus to include additional databases, sources, or selection criteria, thereby providing a more comprehensive overview of the field. Future research could build on this work by repeating the analysis at different points in time, enabling a longitudinal perspective on the evolution of HAI collaboration discourse.

Second, the coding process—based on action and structural codes—entails an interpretative layer. While this approach enables the identification of patterns and relationships across the corpus, alternative coding strategies or analytical frameworks could lead to different categorisations and interpretations. Future studies could explore complementary analytical approaches or compare multiple coding frameworks to further validate and enrich the findings.

Finally, as discussed, a potential misalignment exists between academic literature and design practice, which operate on different temporal scales. While this study captures how HAI collaboration is represented in scholarly discourse, it may not fully reflect how it is currently enacted in practice, particularly in rapidly evolving phases of the design process. Future research could address this limitation by integrating empirical, practice-based investigations to better capture how HAI collaboration unfolds in real-world contexts.

6 Conclusion

This study presented a systematic review aimed at providing a structured overview of the academic debate on HAI collaboration within the design discipline. To achieve this, 48 publications were organised and analysed through a dual coding approach, combining action codes—capturing the approach of each contribution—and structural codes—identifying the topics addressed. Mapping these relationships as a network enabled visualisation of the discourse and identification of distinct clusters, offering a structured lens through which to interpret a fragmented, rapidly evolving field.

The analysis reveals the emergence of distinct research trajectories, in which designing, evaluating, and discussing are unevenly distributed across topics. This results in a concentration of design-driven contributions around applications and contexts of use, evaluation-oriented studies around relational and performance aspects, and discussion-based work around broader implications. While this distribution reflects the exploratory nature of a rapidly developing field, it also points to the need for more balanced trajectories, in which topics are addressed through a combination of designing, evaluating, and discussing approaches.

In this sense, the proposed coding and mapping approach offers a way to frame the HAI collaboration discourse despite its variety and fragmentation. By making visible how different research trajectories take shape, it enables a more systematic understanding of the field and supports the identification of directions for future research. Ultimately, fostering a more integrated balance among practical development, empirical evaluation, and critical reflection may advance more robust, context-aware forms of HAI collaboration in design.

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