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# The Changing Nature of Human-AI Relations: A Scoping Review on Terminology and Evolvement in the Scientific Literature

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## ABSTRACT

Recent years have brought immense progress in the development of AI technology. This broadened its application fields but also led to a surge of interest in many research domains and increasing significance of human-AI relations for the development of AI technology. This rapid growth and evolvement is reflected by the establishment of a great variety of terms, potentially leading to what is known as jingle and jangle fallacies. With our scoping review of the terminology used in scientific literature to describe human-AI relations and its evolvement over time (with 803 records screened, 658 finally included), we capture the variety and development of human-AI terminology in accordance with the shift from *interaction* to *collaboration* between humans and AI. We aim to raise awareness of these developments spanning over different research communities and provide a solid basis for future researchers and practitioners conducting complementary, cross-domain research. Our review comprises terminological, bibliometric and thematic analyses, e.g., reporting on the historical development of terms and term composition patterns, but also identifying key authors and publications, geographic distribution of relevant research, and elaborating on term conception and usage, and co-occurrences throughout the literature.



## KEYWORDS


Scoping review; artificial intelligence; human-ai relations; human-centered ai

## 1. Introduction

The rapid advancements of Artificial Intelligence (AI) technology led to a shift in research and a stronger focus on the humans interacting with AI, establishing a trend towards *human-centered AI* which is also reflected by the wealth of related recent literature (see, e.g., Bingley et al., 2023; Del Giudice et al., 2023; Garibay et al., 2023; Qadir et al., 2022; Shneiderman, 2021, 2022). This *human-centeredness* does not only refer to respecting humans' needs during their interaction with AI, but also to their general role in the relation with AI. While this opens up a lot of interesting research questions and bears potential for significant cross-domain findings, it is especially this interdisciplinarity in combination with the speed of progress that holds a risk for inconsistencies in the terminology used in scientific literature, as explained by Graziani et al. (2023). They point out that inconsistencies between domains frequently occur already in the wording of concepts and illustrate this at the example of “terms such as *interpretable*, *explainable* and *transparent* being often used interchangeably in methodology papers” while they “convey different meanings and are “weighted” differently across domains, for example in the technical and social sciences” (Graziani et al., 2023, p. 1). In

line, Capel and Brereton point out in their recent review (Capel & Brereton, 2023) that *human-centered AI* might range from *explainable* and *interpretable* AI, “[aiding] a human in understanding the decisions or predictions made by the AI” (Capel & Brereton, 2023, p. 5) to humans teaming with AI, where “[t]he strengths of AI and humans complement each other, developing the competencies and capabilities of both” (Capel & Brereton, 2023, p. 8). In addition to these inconsistencies it should also be noted that while terms such as “explainability” are usually positively connoted in the scientific literature, there are also examples of studies that suggest potential detrimental effects (Cabitza et al., 2024, 2023; Ebermann et al., 2023) or at least dissatisfaction (Wang & Yin, 2021). For instance, in case explanations are misleading, they might further cause misjudgement on the user's side (Cabitza et al., 2024). The general terminological inconsistencies impede complementary research and consequently also mutual benefit across domains; we might observe what Block described as the *jingle and jangle fallacies* (Block, 1995). *Jingle fallacies* in this context are terms used ambiguously, leading to the assumption that the concepts they refer to are the same, while they are actually not. *Jangle fallacies* are ambiguities in the other direction, i.e., different terms used for the same concept (Block, 1995).

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The recent intense research interest in AI seems to particularly foster such inconsistencies in terminology. Discussions of ambiguities and a lack of conventions in scientific literature, e.g., Wang pointing out that “there is no widely accepted definition of Artificial Intelligence” and that the term AI “has been used with many different senses, both within the field and outside it” (Wang, 2019, p. 1), but also intensified political discourse ultimately led to the development of standardized definitions, e.g., provided in the European AI Act,<sup>1</sup> where an “AI system” is defined as a

machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments.

or in ISO/IEC 22989:2022,<sup>2</sup> which emphasizes a system’s capability to acquire, process, and apply knowledge and skills. Further, the Organization for Economic Co-operation and Development (OECD)<sup>3</sup> provides a recently updated definition,<sup>4</sup> describing an AI-based system as

machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments.

Further, and in line with the definition in the European AI Act as quoted above, the OECD points out that “[d]ifferent AI systems may vary in their levels of autonomy and adaptiveness after deployment”. However, even though this recent development towards a shared understanding of AI, the fact that inconsistencies used to affect even the general term of AI for years suggests that such issues may be even more pronounced when dealing with specialized, less established terminology in sub-fields of AI. Specifically relating to the *human* in *human-centered AI*, Langer et al. recently studied the effects of terminology and identified considerable differences in humans’ perception and evaluation of systems, introduced through different wording (Langer et al., 2022). They point out that users may judge a system’s competence and technological advancement differently solely based on the terminology used to describe it, which in turn impacts their willingness to adopt or team-up with the system. They compare terms such as “algorithm”, “automated system”, “computer program”, “robot” or “artificial intelligence”, referring to what they subsume under “algorithmic decision-making systems”. Further, Wischniewski et al. in their research on measuring and understanding human trust calibrations for automated systems, point to terminological ambiguities in previous work, explaining that “[a]utomation can refer to various different systems with varying capabilities, ranging from rather simple rule-based to sophisticated machine-learning algorithms” (Wischniewski et al., 2023, p. 4). They also hint that this variety imposed challenges for their study because it was difficult to actually gain insights into the nature of the systems different authors described as “automated”.

The frequent terminological ambiguities related to AI research may have critical implications to society. Benefo et al. describe a set of ethical, legal, societal and economic (ELSE) implications of AI (Benefo et al., 2022). Terminological

transparency is essential for adequate assessment especially when different stakeholders’ perspectives are included. For example, Fernández-Llorca et al. investigate definitions of several key concepts of AI, e.g., AI system, model, or generative AI from a technical and legal perspective and highlight that “[p]recise definitions accessible to both AI experts and lawyers are crucial for the legislation to be effective” (Fernández-Llorca et al., 2024, p. 1). Benefo et al. state that “[a]ny field that could benefit from rapid, aggregate data processing has the potential to be shaped and changed by AI” and that “AI could become an integral part of medicine, economics, policy, scientific research, marketing, customer service, engineering, and beyond” (Benefo et al., 2022, p. 10), indicating the magnitude of the potential ELSE implications. These examples illustrate the urgent need for a shared understanding of concepts and terminology around human-AI relations, eventually resulting in a global terminology as suggested by Graziani et al. (2023). The first necessary step towards this goal is an exhaustive overview of existing terminology across different domains.

In this article, we thus aim at mapping the landscape of the terminology used to describe relations between humans and AI in the scientific literature across time and different communities. We provide a broad overview of terminology usage and its evolution, research coverage and potential research gaps, which may serve as a basis for future research in the field of *human-centered AI*. Further, we derive and analyze thematic clusters in the identified terminology, investigate different geographic origins of certain terms and look into differences in conception and usage. To this end, we perform a scoping review (see a detailed description of the methodology in Section 2) of existing literature with 658 publications finally included, 803 screened. Our analysis is structured in three blocks (terminological, bibliometric and thematic analysis, see Sections 3–5) and guided by eight concrete research questions in total, as described in further detail the following.

First, we aim to provide an overview of the evolvement of the scientific field (not targeting development of AI in general but its use in human-AI relations), resulting in our first research question (RQ1: *How did human-AI terminology evolve over time in the scientific literature?*), also see Section 3.1. Relatedly, we also aim to study the terminology used to refer to what we describe as “human-AI relations” in this article, in the existing scientific literature. We expect this to be of specific interest to the community since several publications (including such just recently published, e.g., Longo et al.’s “manifesto” of open challenges and interdisciplinary research directions related to explainable AI (Longo et al., 2024) from 2024) still point to “inconsistencies” (Graziani et al., 2023), “conceptual confusion” (Longo et al., 2024) or “considerable ambiguity” (Capel & Brereton, 2023) when it comes to terminology, its usage and underlying understandings. We reflect these aspects in our research questions RQ2: *Which term composition patterns can be observed?* (see Section 3.2) and RQ3: *Which terms are used to refer to human-AI relations and how consistent are they?* (see Section 3.3). Based on those, we further investigate terminology in forming thematic clusters (cf. RQ4: *Which thematic clusters can be derived from human-AI terminology?*). Subsequently,

and aiming at identifying the most influential publications and authors researching human-AI relations, and thus also pointing readers to them, we answer our RQ5: *Which key authors and publications can be identified in human-AI literature?* (see Sections 4.1 and 4.2). In addition to our focus on different terminology, its application in scientific work and the underlying concepts, in RQ6, we also analyze our data based on its geographic distribution (*Which geographic differences can be seen in human-AI terminology?*, as discussed in Section 4.3), in order to be able to potentially identify terminological trends that mainly affect specific regions of the world (i.e., continents or countries). Finally, we, in the scope of our thematic analysis of the literature in our corpus, answer our RQ7: *Which themes of term conception and usage consist in human-AI literature?* (see Section 5.1), aiming to provide a deeper understanding of how the various sources use certain terminology (pointing also to specific inconsistencies across specific domains or research fields), and RQ8: *Which semantic associations can be found in human-AI terminology?*, for which we identify popular co-occurrences of terms (see Section 5.2).

## 2. Scoping review

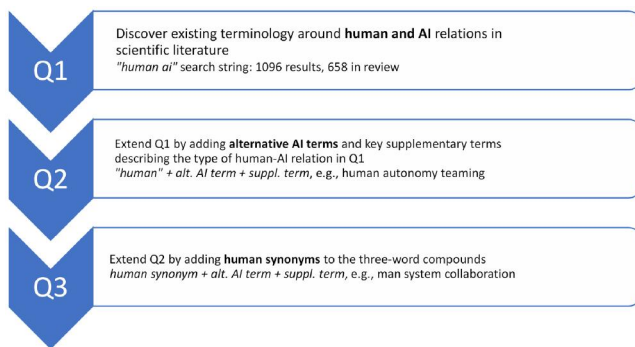
A scoping review of scientific literature typically provides a broad overview of a certain research area. According to Munn et al. it can be used to “identify the types of evidence in a given field”, to “clarify key concepts/definitions in the literature”, to “examine how research is conducted on a certain topic or field”, to “identify key characteristics or factors related to a concept”, or to “identify and analyse knowledge gaps” (Munn et al., 2018, p. 2). Similarly, Arksey and O'Malley point out that scoping studies might be conducted to “examine the extent, range and nature of research activity”, “determine the value of undertaking a full systematic review”, “summarize and disseminate research findings”, or “identify research gaps in the existing literature” (Arksey & O'Malley, 2005, p. 21). According to Peters et al. scoping reviews are commonly used to “clarify working definitions and conceptual boundaries of a topic or field” (Peters et al., 2015, p. 1). Further, they argue that scoping reviews are particularly useful when “a body of literature has not yet been comprehensively reviewed, or exhibits a large, complex, and heterogeneous nature not amenable to a more precise systematic review” (Peters et al., 2015, p. 1). In the context of our research questions raised in Section 1, a scoping review is a great methodological fit: we aim at clarifying terminology and key concepts behind human-AI relations, we strive to analyze potential gaps and clarify conceptual boundaries between different fields, and the body of literature is exceptionally heterogeneous. For our review, we adopted the guidelines defined by Kitchenham and Charters (Kitchenham & Charters, 2007) which have been originally defined for the domain of software engineering (e.g., applied by Kitchenham & Brereton, 2013), and which have been already employed in numerous previous systematic reviews in the broader field of HCI, see e.g., (Butler et al., 2021; de Andrade et al., 2024; Doherty & Doherty, 2018; Kim, Laine, et al., 2021; Neumayr

& Augstein, 2020; Klock et al., 2020; Nunes & Jannach, 2017; Stefanidi et al., 2023; Stepin et al., 2021). This section further explains our process of planning and executing the scoping review. The results are then presented in Sections 3–5.

*Search queries.* Our data collection process contains three queries Q1–Q3 that build upon each other and are successively refined to answer our research questions raised in Section 1. Hereby, the aim for Q1 was to identify all literature that directly combines “human” with “ai”. The query was thus kept as general as possible, to avoid biases as potentially introduced by over-specification of search terms. This query was expected to lead to a large body of results, intended for terminological (see Section 3) and bibliometric (see Section 4) analyses, but also as a basis for the literature-driven extraction of relevant conjunctive terms that can be considered descriptive of human-AI “relations” (e.g., “collaboration” in “human ai collaboration”). This approach was chosen to ensure objectivity in selection of terms describing human-AI relations, and to ensure they actually reflect the existing scientific literature. Q2 then built upon Q1, adding the most commonly used (i.e., in the body of literature extracted from Q1) “relation” terms to the Q1 query (“human ai”), such as “interaction”, “collaboration” or “team”. Additionally, we considerably extended the scope and reach of Q2 by adding alternative terms for the “ai” part of the query, such as “agent”, “system” or “algorithm”. These alternative terms were extracted from the body of literature resulting from Q1. The results of Q2 then were intended as a basis for the analysis historical development and evolvement of terminology in the field (see RQ1 and Section 3.1). Finally, Q3 built upon Q2, again broadening its scope and reach with a focus on the “human” part of the query, by adding commonly used synonyms for “human”, such as “user” (extracted from established dictionaries, see Section 2.3). The results of Q3 built the basis for an analysis of term composition patterns (see Section 3.2). This iterative and reflexive approach (as also depicted in Figure 1) facilitates a general view of the available literature with deeper inspection of specific aspects and is commonly applied in scoping reviews according to Arksey and O'Malley. In total, this process resulted in the accumulation of 36 specific search queries for Q2 (see Section 2.2) and 144 unique queries for Q3 (see Section 2.3). The three queries were conducted between August and September 2024 and are further described in Sections 2.1–2.3.

*Database selection.* Aiming for a broad overview of established terminology in different research domains, we included three databases for data retrieval in our scoping review: Scopus, ACM Digital Library and IEEE Xplore. Two of them (Scopus and ACM DL) have been rated as “principal” search systems by Gusenbauer and Haddaway's systematic evaluation of academic search systems (assessing their suitability for systematic reviews or meta-analyses) (Gusenbauer & Haddaway, 2020). IEEE Xplore, by their review, was assessed as “supplementary” search system (those can be used as supplement to any “principal” system, “where they might still provide great benefit” (Gusenbauer & Haddaway, 2020)). In summary, the ACM Full Text





**Figure 1.** Queries Q1-Q3 subsequently extending the scope to discover a broad overview of the terminology used to describe human and AI relations in scientific literature.

Collection of the ACM Digital Library<sup>5</sup> covers a large proportion of scientific literature in computer science with obvious relevance to human-AI relations. As human-AI relations however are an interdisciplinary field of research, we extended the scope by including Scopus<sup>6</sup> as a broader database covering a wide range of different domains and further the IEEE Xplore<sup>7</sup> database. This is in line with the findings of Bar-Ilan, who highlights the differences in coverage between three databases and urges “to search in multiple databases if there is need for comprehensive data” (Bar-Ilan, 2018, p. 3). She further shows that the overlap of coverage may be smaller than expected and that subject-specific databases, such as the ACM Digital Library, not necessarily offer the most exhaustive coverage for individual search terms within that field (Bar-Ilan, 2018). While Gusenbauer lists Scopus as an interdisciplinary database, we acknowledge that our selected databases still represent a strong focus on Computer Science and Engineering (Gusenbauer, 2022). Future studies, especially those that examine the relations of humans and AI in more depth, may benefit from additional reinforced inclusion of perspectives from, e.g., Sociology and Psychology.

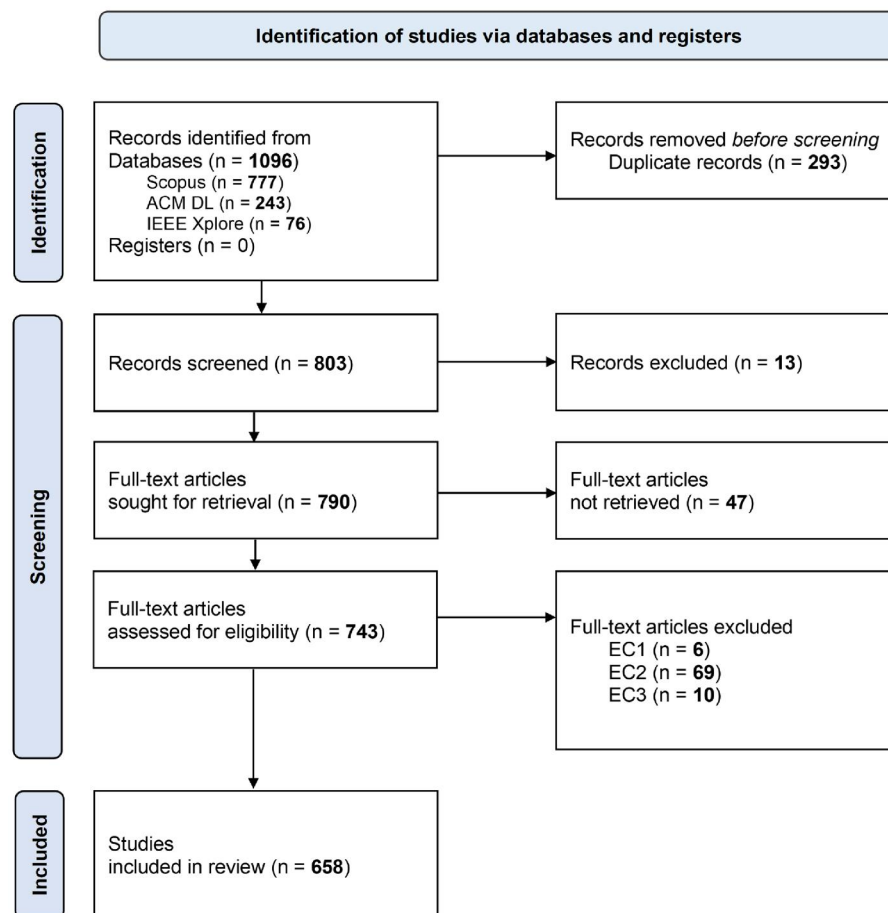
### 2.1. Q1: Overview of terminology on human-AI relations

The first query provides an initial overview of existing terminology. To obtain unbiased results, we tried to avoid assumptions in data collection and framing of the review. To satisfy this objective, we decided for a broad search term for the initial query, including both “human” and “AI”, as explained in detail above. We ran exploratory queries prior to the actual review to find a search string broad enough to capture the variety of human-AI literature yet narrow enough not to include unprocessable amounts of irrelevant data. These preliminary queries included specific aspects of or designations for human and AI relations, e.g., “human-AI interaction” and “human-AI collaboration”, which certainly would miss broader parts of human-AI literature. Concurrently, we experimented with more general approaches, e.g., using the selected databases’ standard search options without the requirement of an exact match. Too broad searches returned an unmanageable amount of data, including many irrelevant

publications. With “AI” as a common abbreviation of “Artificial Intelligence” (note: case-insensitive), we found “human AI” to be a suitable search string covering a large variety of human and AI relations.<sup>8</sup> The reverse order, “AI human”, yielded a smaller number of results. Further, we hypothesized based on preliminary queries, that the reversed order in “AI human” may implicitly associate differences in authority. Also, the results using this version of the query contained a lot of false positives where “human” directly followed “AI” without any direct semantic connection, e.g., “[...] ethical AI: human rights [...]”. The final search string was thus defined to be “human AI” and searched for as an exact phrase in titles only. We defined the criterion for inclusion of relevant data in our scoping review as follows:

- IC: Presence of a specific human-AI term in the publication’s title, including both “human”, “AI” and a supplementary term indicating a human-AI relation.

We applied a rule-based approach to ensure structured inclusion of data that is relevant to our scoping review on human-AI terminology. This approach supports transparency and clarity in decisions of whether or not to consider a term and include the respective publication. One main researcher judged the resulting publications based on the inclusion criterion and marked ambiguous cases for group discussion to minimize potential researcher bias, making the process consistent with the vast majority of other reviews in the field (e.g., Butler et al., 2021; de Andrade et al., 2024; Kim, Laine, et al., 2021; Neumayr & Augstein, 2020; Nunes & Jannach, 2017; Stefanidi et al., 2023) as pointed out by Stefanidi et al.’s review of reviews in HCI (Stefanidi et al., 2023). The presence of a human-AI term was considered if “human”, “AI” and one supplementary term connecting the two was present. This led to the inclusion of publications using “human-AI interaction”, where interaction is the supplementary term connecting human and AI. In contrast, the presence of human, AI and a supplementary term in a sentence was not sufficient: “humans interacting with AI” was not considered a valid term. We further included terms which did not follow our three-part compound scheme, but describe known concepts and are therefore established in the scientific literature, as for example “human-centered AI”. Note that the inclusion of these terms did not result from additional searches, as that would contradict the *systematic* search strategy. Some publications used descriptive terms, e.g., adjectives indicating the nature or focus of the human-AI relation (e.g., trustworthy, collaborative) or additional words specifying the context (e.g., human-AI *music* co-creation). Such cases were included if they were directly connected to the term, i.e., placed immediately before or within the three-part compound term, and were considered relevant to the focus and understanding of the term. Disregarded adjectives mostly concerned cases where publications aimed to improve a named concept, and therefore used “better”, “enhanced” or similar adjectives.



**Figure 2.** Modified PRISMA flow diagram showing the review process for Q1. 658 of 1,096 initially identified records were finally included.

Publications were excluded from the review if they met at least one of the following three Exclusion Criteria (EC):

- EC1: The retrieved item is a non-English language publication.
- EC2: The retrieved item is a non-scholarly publication of four or fewer pages (e.g., workshop proposals).
- EC3: The retrieved item is not a single publication (e.g., retrieved items are collections containing multiple workshop papers).

We excluded non-English publications (EC1) to avoid bias due to translation issues and the resulting impeded comparability. Regarding EC2, we excluded particularly short papers such as proposals, invitations or abstracts. While they may use relevant terminology, their scope likely is insufficient for later content-related analyses. EC3, in contrast, concerns collections of several papers or articles, such as books containing chapters, or workshop proceedings containing workshop papers. Our unit of analysis consists of single publications. We, therefore, include individual book chapters, workshop papers of sufficient length, journal articles, conference papers and reports but not the collections per se.

The PRISMA flow diagram in [Figure 2](#) summarizes the data retrieval process for Q1. All items were screened by one main researcher (the first author) to avoid discrepancies in assessment; however, uncertain cases were discussed in a group of three of the authors to find objective consensus, as described above.

Q1 was executed across the selected databases from August 7 to 15, 2024, leading to 1,096 results (Scopus: 777, ACM Digital Library: 243, IEEE Xplore: 76), of which 293 duplicates were identified across and within the databases, which were consequently removed. Of the remaining 803 items, 13 did not fulfill the inclusion criterion. In one case, a term technically fulfilling the previously defined pattern was found, but concerned specific proteins (“ai”) in humans, published in the field of biology (e.g., Fidge et al., 1989; Morrison et al., 1990). Full-texts of 790 items were sought for retrieval and, if not directly available via the publisher, searched for using Google’s search engine, authors’ websites and ResearchGate.<sup>9</sup> For 47 items, full-texts could not be retrieved, which resulted in 743 publications with full-text available. Further, six articles not written in English were excluded (cf. EC1), and 69 were excluded as they did not qualify as scholarly publications (e.g., workshop invitations, abstracts or position papers, cf. EC2). Ten items were collections rather than individual items and were therefore excluded (cf. EC3).

During the screening process, we extracted all human-AI terms in harmonized form, i.e., removed special characters and aligned singular and plural forms as well as different spelling of the same term, from the publications' titles. This resulted in a total of 253 unique extracted terms for further analysis (see Sections 3–5). The frequency distribution of the terms showed only few very prominent terms and a great variety of terms with only single occurrences (maximum: 139, minimum: 1, mean: 2.6, median: 1) resembling a long tail distribution (Anderson, 2006). Terms with highest frequencies were “human-AI collaboration” (139 occurrences), “human-AI interaction” (94), “human-AI team” (31) and “human-AI teaming” (30), where the very strong popularity of few terms already becomes obvious. The conjunctive terms of the most prominent human-AI terms were later integrated into search string construction for Q2 (see below). “Team” and “teaming” were handled as separate terms as they differ regarding the application domain (Capel & Brereton, 2023): “team” is used for decision-making in which humans seek complementarity rather than relying on one individual decision maker's capabilities, while “teaming” is more related to co-creation and creativity.

*Subset for thematic analysis.* For the thematic analysis in Section 5, we extracted terms that occurred at least three times in our Q1 data as to capture more established terms rather than just single occurrences. Of each of these terms, we drew a sample of a maximum of five publications per year by citation count to represent the data appropriately. This reduced the amount of publications from 139 to 29 for “human-AI collaboration” and from 94 to 28 for “human-AI interaction”. We decided for this approach to ensure to capture relevant terminology in human-AI relations rather than outliers. At the same time however, novel discussions may be left out by this decision, as related terminology may not yet be sufficiently established to be reflected in publications' titles. To explore the origin and emergence of novel terms in more detail, thorough analysis of full-texts rather than titles may be required.

## 2.2. Q2: Alternative AI terms

The notably short temporal coverage of Q1 data with publication dates only ranging from 2011<sup>10</sup> onwards (see Section 3) indicated that other terms might have been used to describe human and AI relations in earlier literature. Following the commonly reflexive nature of scoping reviews (Arksey & O'Malley, 2005), we therefore decided to extend our query with alternative AI terms, aiming to consecutively cover the area of interest more comprehensively. We derived alternative AI terms from all identified records of Q1 and consulted online dictionaries and thesauri such as Merriam-Webster<sup>11</sup> and PowerThesaurus<sup>12</sup> and the list of terms provided in the EU-U.S. Terminology and Taxonomy for Artificial Intelligence<sup>13</sup> to finally obtain a set of eight unique alternative AI terms, shown in the second column of Table 1. We further sought alternative terms for “AI” and similar systems by screening literature reviews. The

**Table 1.** Alternative terms for “AI” and “human”, and most prominent conjunctive terms describing relations between humans and AI (listed in alphabetical order).

Human terms	AI terms	Conjunctive terms
Human	Agent	Collaboration(s)
Man	Ai	Interaction(s)
Person	Algorithm	Teaming
User	Autonomy	Team(s)
	Computer	
	Machine	
	Robot	
	System	
	Technology	

identified terms were either focused on specific applications, e.g., “reasoning”, “recognition” and “segmentation” (Hirzle et al., 2023), and did not represent AI in general, or were more specific definitions of system or program, as in “decision support system” and “computer program” (Langer et al., 2022). Thus, our list of alternative AI terms was not further extended.

*Q2 search string construction.* We first combined “human” with each of the extracted alternative AI terms. As this would lead to large amounts of irrelevant data, e.g., “human agent” would likely refer to an agent of human nature, not the combination of a human and an agent, we added the most prominent conjunctive terms from Q1 data (see Table 1) and formed three-part compounds, e.g., “human agent interaction” or “human system collaboration”. While this constraint again narrowed the scope, the distribution of term frequency in Q1 showed that large parts of human-AI literature were covered by these terms. We manually evaluated the queries' results to ensure their effectiveness. Cases of uncertainty were resolved in group discussions and more in-depth evaluation. For example, combinations with *autonomy* as the alternative AI terms were checked thoroughly to indeed refer to human-AI relations rather than the autonomy of humans (see also Section 3.1). A total of 36 individual queries were performed for each database within Q2, with search strings including singular and plural versions of the conjunctive terms (e.g., “collaboration” and “collaborations”). For our analysis, the result counts per individual term composition were essential. For this reason, we only used Boolean operators to combine singular and plural versions of the same conjunctive term, e.g., “human agent collaboration” OR “human agent collaborations”. A comprehensive overview of all queries and result counts of Q2 and Q3 (see Section 2.3) is available in the [Supplementary Material](#).

*Q2 result counts.* For Q2 and Q3, only the result counts per query, and for Q2 per year were collected, as the goal was different from Q1, and the number of queries led to unmanageable amounts of publications to analyze individually. The reduction to result counts is suitable for giving broad overviews, however, it should be noted that a certain share of irrelevant data may be included. We intentionally disregarded certain terms that yielded an unmanageable number of results, where a large part can be expected to be false positive as these terms are known to be widely used in contexts other than AI. We investigated this expectation prior to our actual search and e.g., found more than 6,200

**Table 2.** Overview of search strings, included terms and result counts for Q1-Q3.

	Q1	Q2	Q3
Individual Queries	1	36	144
Results Retrieved	1,096	20,341	20,881
Results Included	658	2,755	3,295
Databases	Scopus, IEEE, ACM DL	Scopus, IEEE, ACM DL	Scopus, IEEE, ACM DL
Searched In	Publications' Titles, Exact Match	Publications' Titles, Exact Match	Publications' Titles, Exact Match
Human Terms	Human	Human	Human, Man, Person, User
AI Terms	AI	Agent, Algorithm, AI, Autonomy, Computer, Machine, Robot, System, Technology	Agent, Algorithm, AI, Autonomy, Computer, Machine, Robot, System, Technology
Relation Terms	None	Collaboration(s), Interaction(s), Teaming, Team(s)	Collaboration(s), Interaction(s), Teaming, Team(s)
Example Query	"human ai"	"human agent collaboration" OR "human agent collaborations"	"user ai teaming"

results for the term *Human-Computer Interaction(s)* (see below), 4,600 in one single database (Scopus). Similarly, a query for *Human-Robot Interaction(s)* yielded more than 7,300, and for *Human-Robot Collaboration(s)* more than 2,200 results. Subsequently we estimated the false positive rate based on further queries adding requirements of occurrences of "AI" in title, abstract or keywords of the articles. For instance, on Scopus only about 180 of the 4,600 articles fulfilled this criterion, suggesting an overall false positive rate of more than 96%. After these preliminary test runs, we thus excluded the following terms:

- *Human-Computer Interaction(s)*, *Human-Machine Interaction(s)* and *Human-Robot Interaction(s)*: these are strong research fields regarding the interaction between humans and different systems, which not necessarily relate to AI. The broadness of these research fields may introduce separate terminology, which enables further cross-domain investigations but exceeds the scope of our review of human-AI terminology.
- *Human-Robot Collaboration(s)*: This mostly concerns the collaboration between humans and industrial robots and can arguably be regarded a separate research field.

In total, we retrieved 2,755 results for Q2 (Scopus: 1,962, ACM Digital Library: 358, IEEE Xplore: 435): 580 for combinations with "robot", 469 for "machine", 521 for "agent", 626 for "AI", 166 for "system", 100 for "technology", 215 for "autonomy", 61 for "computer" and 17 for "algorithm". Note that as reasoned above, combinations with "robot" (2,255 results across databases) were removed from result counts for "collaboration(s)" as were combinations with "computer" (6,233), "machine" (1,765), and "robot" (7,333) for "interaction(s)".

### 2.3. Q3: Alternative human terms

Although not present in our Q1 data, it is most likely that alternative human terms exist, which could further enhance the comprehensiveness of our scoping review. After using Power Thesaurus<sup>14</sup> and DeepL Translator<sup>15</sup> to identify synonyms, we included "person" and "man"<sup>16</sup> as general terms as well as "user", considering the context. Three-part compounds were formed as in Q2, connecting all terms of all

columns in Table 1. This resulted in unique search strings like "human agent collaboration" and "person system teaming" (all individual queries and their result counts per database are listed in the [Supplementary Material](#)). For each of the selected databases, 144 individual queries were performed, from which only the total result counts were retrieved. Overall, 20,341 items were retrieved (Scopus: 14,147, ACM Digital Library: 1,862, IEEE Xplore: 4,332), which we visualized to analyze term composition patterns in human-AI terminology in Section 3.2.

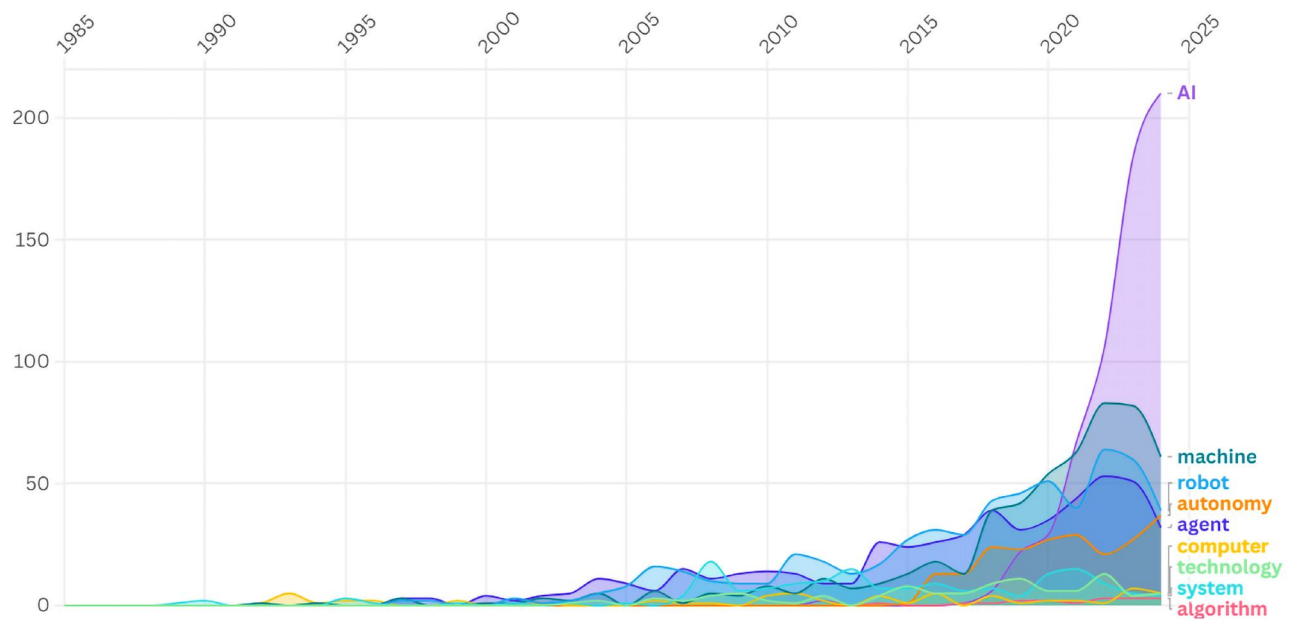
Table 2 summarizes the specifics and differences of queries Q1–Q3. All queries were applied to the same set of databases as exact matches in publications' titles. Differences can be seen in the expansion of the search strings and resulting numbers of retrieved and included items in the review. While Q1 search string only contains human and AI (resulting in "human ai"), both Q2 and Q3 use a set of different potential AI terms in combination with terms that describe the relation between humans and AI, e.g., collaboration or interaction. Q3 further contains synonyms for *human* to further extend the scope. The numbers of retrieved and included items per query show a strong increase in scope when including different AI terms from Q1 to Q2 while the exclusion of highly generic terms (e.g., HCI) is reflected in the drastic gap between retrieved and included items in Q2 and Q3. The inclusion of synonymous human terms did not substantially expand the scope further.

The following sections contain results of our analyses structured in three blocks. Section 3 gives an overview of the terminology, its development and derived topics of interest. Later sections include analyses of influential authors and publications and the geographic distribution of contributions (Section 4) and more in-depth thematic analyses focusing on the conception, usage and co-occurrence of the found terms (Section 5).

## 3. Terminological analysis

Analyses in this section are based on the presence and phrasing of terms in human-AI literature. In Section 3.1, visualizations of data obtained through Q2 and Q3 show the temporal development of term usage, Section 3.2 shows term composition patterns using alternative human- and AI-





**Figure 3.** Development of the popularity of different terms in the human-AI context ranging from 1989 to September 2024 with respective publication counts on the y-axis. Alternative AI terms were extracted from Q1 results. Terms describing separate research fields, e.g., HCI, were excluded for this visualization.

terms. We investigate the variety of human-AI terms found through Q1 in [Section 3.3](#) and form thematic clusters in [Section 3.4](#).

### 3.1. Historical development

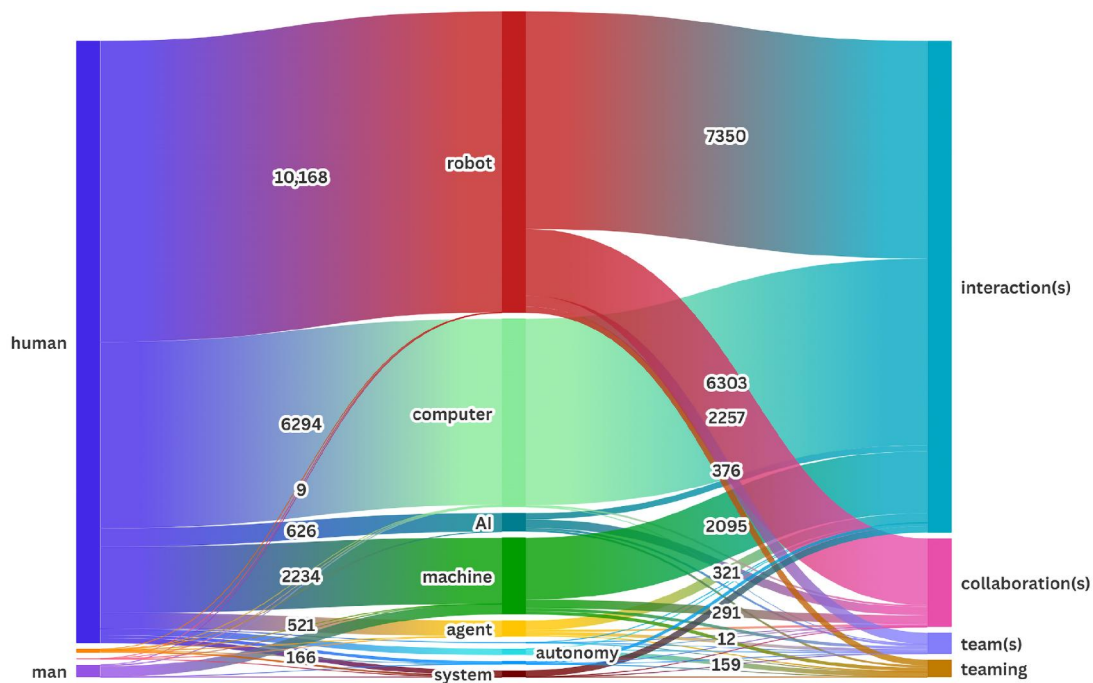
Developments such as the shift of AI research towards complementarity between humans and AI are likely represented in dynamically changing terminology. As the terms in use often implicitly convey characteristics and influence the perception of the AI system (Langer et al., 2022), we investigate with RQ1 whether and how human-AI terminology has changed over time, including alternative terms and term combinations.

*RQ1: How did human-AI terminology evolve over time in the scientific literature?* We first investigate Q1 data, where earliest retrieved items were published in 2011 and 2012. The initial sparse coverage is followed by an almost exponential increase in publication counts from 2017 to 2023.<sup>17</sup> We concluded from this rapid development and the apparent gap before 2011 that “human-AI” terms may have evolved with the shift towards human focus and complementarity, and that other terminology may have been popular before.

We first focused on “AI” possibly being a trending term with less prominence in earlier research. In Q2, we therefore searched for alternative terms (see [Section 2.2](#)) describing similar topics before the sharp increase in human-AI research interest. We used alternative AI terms in combination with the key supplementary terms (see [Table 1](#), e.g., “human algorithm teaming”). [Figure 3](#) shows absolute numbers of publications summed per alternative AI term (e.g., for “algorithm”, results stem from queries including “human”, “algorithm” and each of the key supplementary

terms). We excluded combinations that are popular terms in other research fields and less specifically relevant to human-AI relations, such as “Human-Computer Interaction”, from this visualization (see also [Section 2.2](#)). Still, “computer” remained in the visualization, as e.g., “human-computer collaboration” may indeed refer to collaborative AI systems. The remaining sparsely covered area in the visualization indicates that “computer” is mainly associated with interaction rather than collaborative approaches. We used the same procedure for combinations of “machine” and “robot” with “interaction” as well as “robot” with “collaboration” (cf. [Section 2.2](#)). The graph still shows large areas for remaining combinations with “machine” and “robot”, indicating that research in these fields goes beyond interaction. We specifically reviewed “human-autonomy” combinations, double-checking whether they actually refer to a relation, not the autonomy of humans (despite our search terms being quite specific). Against our expectations, all publications in our sample actually used the term to refer to a relation between humans and autonomous systems, most prominently, autonomous aviation (Demir et al., 2019) and marine (Thieme & Utne, 2017) systems, indicating it might be specific to these domains. [Figure 3](#) further shows that some terms were used consistently with small fluctuations throughout the years, e.g., “robot” and “agent” with large proportions of the overall data, or “computer”, “system” and “technology”, covering small proportions. Other terms emerged in recent years (“AI”, “algorithm”, “autonomy”) or experienced a sharp increase in research interest (“AI”, “machine”), with publication counts for “AI” exceeding other combinations greatly in recent years.

[Figures A1\(a to i\)](#) (see [Appendix A](#)) allow for a more detailed analysis of the development of human-AI terminology by splitting up Q2 data with respect to the individual



**Figure 4.** Initial Sankey diagram showing connection strength of different three-part compound terms (left: alternative *human* terms, middle: alternative *AI* terms, right: most popular *supplementary* terms).

AI terms and supplementary terms (Table 1, second and third column). Note that Figures A1(g) (related to “robot”), Figure A1(f) (related to “machine”) and Figure A1(e) (related to “computer”) do not include “interaction” and Figure A1(g) does also not include “collaboration”, as mentioned earlier. Therefore, the respective dashed lines represent only zero-values. Earliest data is available for combinations with “computer” (without combinations including “interaction”) and “system”. Combinations of both “system” and “technology” with “interaction” are steadily covered over time, with an increase after 2005 of “system” followed by an increase of “technology”. This may be due to significant technological advancements around that time, such as the emergence of cloud computing (García-Valls et al., 2018) and increased popularity of smartphones (O’Regan & O’Regan, 2008). Further increases can be found for “human machine collaboration” around 2014 and 2017, followed by a remarkable rise of “human AI collaboration” popularity starting around 2017, indicating a strong shift towards collaborative relationships.

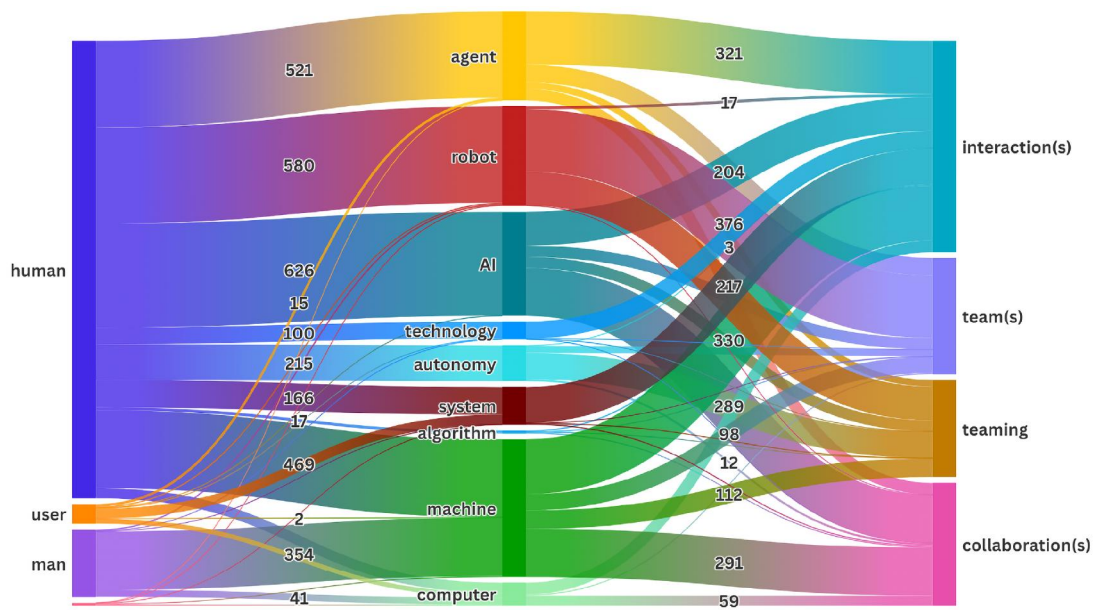
### 3.2. Term composition

In multi-part terms, term composition patterns and frequent combinations may give information about the attributed properties of combinations, for example, competence or sociality in the context of “human” and “AI” combinations. RQ2 concerns observed patterns in human-AI terminology.

RQ2: Which term composition patterns can be observed? As explained in Section 2.3, we combined all human, AI and supplementary terms to three-part compounds, e.g., “human agent collaboration” or “user computer interaction”

in Q3. Figure 4 shows the connections between all included terms and gives a general overview of commonly used combinations. Strongly dominant terms are visualized with large bars, where the size is determined by the connection strength to each of the terms in the neighboring column. The magnitude of “human” and “interaction” in comparison to all other terms is particularly noticeable. This again stems from a certain combination of terms, e.g., “Human-Computer Interaction”, referring to separate research fields that do not necessarily concern human-AI relations. For this reason, we removed these compounds in Figure 5 to obtain a less cluttered view and set a focus on the apparently less dominant, yet relevant terms.

There are two perspectives to this more detailed view. The connections between the first and second column show which human synonyms are combined with which potential AI terms. E.g., the connection to “user” is stronger for “system” and “computer”, while barely present for the other terms. This links to “computer” and “system” typically being used in combination with “interaction”, as shown previously in Section 3.1. Combinations with “user” may indicate a lesser degree of autonomy and collaboration between humans and AI, unidirectional communication and focus more on a tool- rather than partner-relationship. “Man” specifically shows connections to “machine”. This combination comes from earlier research conducted decades ago, where “man” was used as synonymous for “human” (among them Licklider’s prominent early vision of “man-computer symbiosis” (Licklider, 1960) or Sutherland’s likewise prominent description of a “man-machine graphical communication system” (Sutherland, 1963). The connections between the second and third column show the relation that is mostly



**Figure 5.** Connection strength of different terms after removing terms of separate research fields. A less cluttered view allows for different views on the connections and conclusions on the nature of the connections to be drawn.

seen between humans and the respective alternative AI term. Notably, “autonomy” is strongly connected specifically to “teaming”. This indicates “human autonomy teaming” being an established term, which emerged from “human automation interaction” according to Lyons et al. (2021). “AI” shows the strongest connection to “collaboration”, mostly stemming from the recent surge in research interest as shown in Section 3.1. The overall picture given by this visualization is a likely collaborative, bidirectional partnership between humans and AI, contrary to terms connected to “user” on the left side of the diagram tending to focus on “interaction” rather than “collaboration”, which supports the assumption of rather unidirectional tool usage.

### 3.3. Human-AI terminology

Given the rapidly increasing popularity of explicit *human-AI* terminology in Section 3.1, RQ3 suggests an overview of the variety of supplementary terms specific to human and AI relations.

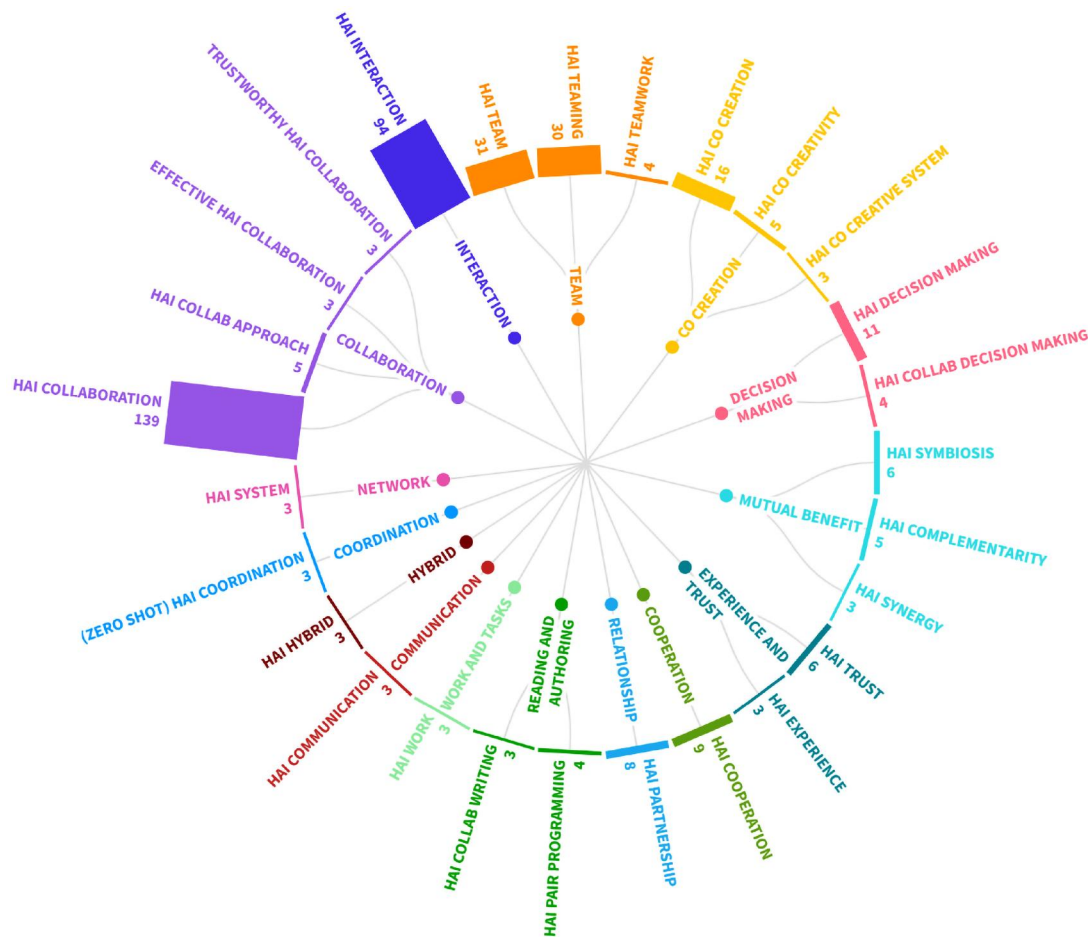
RQ3: *Which terms are used to refer to human-AI relations and how consistent are they?* For this initial overview, we extracted all terms during the screening process of Q1 (see Section 2.1) in a harmonized form to reach 253 unique terms. We included words descriptive of the task or application of the human-AI relation in brackets, whereas adjectives were considered part of the term if they satisfied the pattern for human-AI terms described in Section 2.1. Table B1 contains a list of individual terms (third column). Note that, due to the inclusion of descriptive words, the table may include seemingly redundant terms, such as different terms including *interaction*. For a less cluttered view, Figure 6 shows only the most prominent terms (i.e., those with more than two occurrences in our Q1 data). It becomes clear that only few of the large amount of individual terms occur more than twice in our data at all, which may reflect the essential research focus in human-AI relations. The

inclusion of descriptive words and adjectives may provide additional insights into term usage, existing challenges or research goals and potentially affect term conception, while the strong popularity of few terms remains clearly discernible in Table B1. Further, we hypothesize that a large amount of individually used terms in combination with few prominent terms in a yet evolving field may stem from the ongoing development and search for conventions, with a variety of emerging terms and few trending ones rapidly gaining popularity. To investigate this further, we focus on thematic patterns in the usage of popular terms in Section 5.1. Note that this overview is specific to terminology explicitly using “human-AI” combinations, given our search string for Q1. Human-AI relations are further referred to with a variety of terms that are not included in this view even though they may be highly relevant, e.g., hybrid intelligence (Dellermann, Ebel, et al., 2019). While including *all* possible terms may be infeasible in terms of systematic searches and exceeds the scope of our review, our overview may serve as a starting point for further analyses.

### 3.4. Thematic clusters

The given terminology may include similar terms or topics, from which we derive thematic clusters with respect to RQ4. In the later thematic analysis we aim for deeper analysis of the actual usage, conception and interpretation (see Section 5.1), which may hint towards hidden similarities or differences as well as jingle and jangle fallacies between terms.

RQ4: *Which thematic clusters can be derived from human-AI terminology?* Clustering based on the terminology used in a specific field can unveil frequently discussed challenges and opportunities, applications and domains. We clustered the terms extracted through Q1 based on terminological and semantic similarity, following a human clustering approach inspired by what Holtzblatt et al.



**Figure 6.** Excerpt of prominent terms in human-AI relations stemming from Q1 data. All terms with more than two occurrences are included in this visualization, along with the respective subcluster. An overview of all terms is available in Table B1 in Appendix B.

(2005) describe for their “affinity building” phase within the Contextual Design methodology. As a first step in this process, one main researcher judged similarities to find initial clusters. Then, a group of three researchers, including the one that did the first clustering (all among the authors of this article) discussed and rearranged the clusters in an interactive team process to find consensus. This process facilitated transparency and structure, and mitigated researcher bias despite human judgment. We identified a total of 30 clusters, which then were clustered again in four resulting higher-level clusters: *Applications*, *Connection*, *Design* and *Working Together*. Subsequently, the 30 clusters (see Table B1, second column) will be referred to as subclusters. The four main clusters with their respective subclusters are described in Sections 3.4.1 to 3.4.4, the concrete assignment of publications to (sub)clusters can be found in Table B1 in Appendix B. While some of the clusters are clearly larger than others, this does not necessarily mean that the same proportion of our corpus of literature concerned this cluster. More accurately, these clusters can span a wider range of different individual terms, which could reflect research interest in the area, great focus on adjectives describing individual terms, but also hint a lack of accepted conventions.

### 3.4.1. Connection

Terms in this cluster may indicate social connections such as friendship or partnership but also include differences and dissimilarities as well as complementarity and resulting benefits. The concrete subclusters (highlighted in bold below) can be described as follows. In contrast to the commonly collaborative and target-oriented nature of teams, the concept of **Relationship** does not necessarily imply working towards a shared goal, but may include friendships and intimate relationships (Brandtzaeg et al., 2022), that indicate some degree of social binding. **Integration** relates to a seamless combination of humans and AI. **Mutual Benefit** may refer to synergistic effects and complementarity of humans and AI, taking advantage of each others’ capabilities. **Network**, e.g., including human-AI “(eco)systems”, can be seen to describe the connection between humans and AI regarding their communication and information sharing. **Hybrid** “approaches” and “systems” imply bi-directional contribution of human and AI parts and may partially be seen as a degree of involvement. As “hybrid”-terms were frequently used to describe the union of humans and AI as one, we decided to create a separate subcluster. **Team** is the most prominent subcluster with several terms related to teams, teamwork and teaming constellations with human



and AI teammates. We included “team” and “teaming” as separate terms, as Capel and Brereton explain different contexts: “teaming” is associated with a more creative context, whereas “team” is used for decision making in which humans do not want to rely on their own or the AI’s decision alone, but take advantage of the complementarity (Capel & Brereton, 2023).

### 3.4.2. Working together

This cluster contains the aspects commonly associated with Computer Supported Cooperative Work (CSCW). The focus of this cluster is collaborative work and creation, including topics such as task distribution as well as ways of communication and interaction between humans and AI. There are many different approaches how to define and interrelate individual concepts in the CSCW domain, such as collaboration and cooperation. According to Schmidt and Bannon, cooperation involves interdependence of tasks with *different* goals, while collaboration involves joint work on resources with *common* goals (Bannon & Schmidt, 1989; Schmidt & Bannon, 1992). Dillenbourg distinguishes cooperation and collaboration based on task distribution (“In cooperation, partners split the work, solve sub-tasks individually and then assemble the partial results into the final output. In collaboration, partners do the work ‘together’” (Dillenbourg, 1999, p. 8)) as well as cognitive processes (Dillenbourg, 1999). We mostly follow the structure and nesting of CSCW concepts proposed by Shah (2010). **Collaboration** implies productively working on a shared goal including task-related communication, interaction and task distribution to reach complementary performance. **Cooperation** is one essential part of collaboration and includes contributing together to a shared goal (contrary to the categorization of Schmidt & Bannon, 1992; Bannon & Schmidt, 1989). In contrast to collaboration, the outcome does not exceed the result of the shared contributions (Shah, 2010). **Coordination** is nested within cooperation according to Shah (Shah, 2010) and includes communication and task distribution (which are described as separate subclusters) to ensure smooth collaboration and the best usage of resources within a team. **Communication** as an essential part of coordination may concern communication direction, modalities and interfaces. We also included conversation in this cluster if the term indicated a focus on the peculiarities of communication between humans and AI, while terms focusing on application cases of *dialog systems* are found in the *Applications* cluster. **Co-creation** can be seen as a specific collaboration aiming at joint creation, often of innovative or creative content, e.g., “music co-creation”. **Task Distribution** is another aspect of coordination, while **Work and Tasks** focuses on the joint work or specific tasks and their implications rather than their efficient assignment. Terms in the **Interaction** subcluster mainly focus on the way and nature of interaction and also include dynamics, interplay and interactive approaches. **Experience and Trust** in human-AI relations may influence appropriate reliance and the willingness to work together.

### 3.4.3. Applications

Several publications reflected specific application cases of human-AI relations in their titles. Human-AI **Decision Making** includes both parties to find decisions based on hybrid knowledge. The **Learning** subcluster involves learning and teaching. Learning includes joint efforts to support human learning (van den Bosch et al., 2019) as well as mutual learning about the collaboration partners (Schoonderwoerd et al., 2022). **Control** rarely reflects the intuitive interpretation of human control and autonomy in the interaction with AI (Lundberg et al., 2021), most terms in this cluster rather describe a complementary approach of sharing control of some external aspect, e.g., the switch from one learning situation to another (Echeverria et al., 2020; Li, Huang, et al., 2022). The subcluster **Reading and Authoring** suggests reading, writing and editing as collaborative applications with focus on interaction dynamics (Yang et al., 2022), capabilities of large language models (LLMs) (Lee, Liang, et al., 2022) and complementarity during the respective process (Chen, Wu, et al., 2023). **Dialog Systems** include conversational systems and chatbots. **Data Processing and Analysis** includes collaborative approaches of humans and AI aiming to facilitate data analysis, e.g., by coding and labeling (Brachman et al., 2022; Gebreegziabher, Zhang, et al., 2023). Publications regarding human-AI **Sensemaking** are either directed towards the mutual understanding of the interaction partners themselves to be able to interact and collaborate effectively (Shen et al., 2021) or towards the shared effort to make sense of some external, complex data (Dorton & Hall, 2021). **Collaborative Design** refers to applications where humans and AI design together, rather than the design of human-AI interactions as describes in the *Design* cluster and respective subcluster. **Exploration and Detection** includes joint detection of patterns or information (Schmitt et al., 2024; van Zoelen et al., 2023) and exploration of design spaces (Viros-I-Martin & Selva, 2021). Terms which describe specific application cases outside the scope of the described subclusters and were only found once in the data even after harmonizing the terms were collected separately in a **Miscellaneous** pool.

### 3.4.4. Design

This cluster focuses on foundations to build on, guidance for practitioners or researchers and guidelines to be followed to potentially support the development of suitable solutions for interaction and collaboration between humans and AI. **Design** terms mostly concern frameworks and interfaces (Guimaraes et al., 2021; Marhraoui et al., 2022), protocols and workflows (Fogliato et al., 2022; Liu et al., 2020).

## 4. Bibliometric analysis

Identifying key authors and publications in a field can reveal developments initiated by influential researchers or networks among them, as well as key findings that may have strongly influenced the research landscape. In the context of this

work, emerging terminology may have been shaped by highly popular publications. To complement the findings directly related to the terms themselves, we thus conducted a bibliometric analysis (cf. RQ5), aiming at focusing on a small number of both authors and publications, in order to specifically point readers to them. Due to the high number of overall publications in our review, these outstanding researchers and pieces of work would be hard to localize in the corpus otherwise.

*RQ5: Which key authors and publications can be identified in human-AI literature?* We extracted key authors and key publications from Q1 data, based on numbers of publications they were involved with for key authors and citations for key publications as metrics. We considered not only absolute, but also average citation counts per year for publications.

#### 4.1. Key authors

We identified key authors on the basis of Q1 and referring to the number of publications the individual authors were involved in, where authorship was generally considered regardless of the authors' order or role in the papers. Overall, 2,254 individual authors were found, 589 of which were first authors in at least one publication. Most authors (1,958) contributed to only one publication. Table 3 shows the key authors listed by publication counts including their affiliations and publications. We selected all authors within the 99th percentile of publication counts in our corpus of literature (please note that several authors have identical publication counts). Most of the selected key authors contributed as *first* authors in only a small share of their publications. Notable exceptions are António Correia and Jeba Rezwana who are both listed as first authors for six of their seven publications shown in Table 3.

#### 4.2. Key publications

Key publications are relevant to a comprehensive understanding of the research landscape and its development. The large impact of, usually, a small number of outstandingly influential, publications can be observed by their absolute citation count on one hand (which is however generally biased with regard to publication date), which indicates that a large portion of the literature refers to concepts and findings described in these publications. On the other hand, citation counts could also be averaged per year, which allows for a more inclusive approach related to more recent publications (we acknowledge that this reduces but does not fully remove the aging bias which generally prevails in such listings). Additionally, differences in coverage of different databases may however influence the computation of citation counts, as Bar-Ilan states that “each database draws the citations only from the items covered by it” (Bar-Ilan, 2018, p. 3). Further, databases may show differences regarding publication type of most frequently cited publications. Bar-Ilan shows that proceedings being a popular publication format

in computer science is reflected in the most cited publications in the ACM Digital Library in comparison to the popularity of journal articles in Scopus (Bar-Ilan, 2018). For better comparability of publications from the different databases, we therefore retrieved citations counts from Google Scholar using SerpAPI's Google Scholar API.<sup>18</sup> Table B2 in Appendix B shows both total (cumulative) and average (per year) citation counts per publication along with extracted keywords and a brief summary.

Tables 3 and B2 show little overlap: only two publications (Amershi et al., 2019; Bansal et al., 2019a) are also found in the publications of key authors. Notably, both are joint efforts by researchers affiliated with Microsoft Research, indicating the institution's impact in the field. The publications mainly focus on complementarity, perception and interaction in human-AI relations. Designing and facilitating human-AI interaction seems particularly challenging yet crucial for complementary performance. Besides interaction design, human perception greatly impacts team-up willingness. Overall, the key publications show a collective shift towards working together rather than competing against each other, aiming for performance that neither of the parties could reach alone.

#### 4.3. Geographic analysis

The worldwide distribution of researchers within a research field implies a variety of cultural backgrounds, local developments and research directions. By conducting a geographic analysis of their affiliations, we investigate the geographic distribution of human-AI terminology but also focal areas and global coverage of the overall research field to answer RQ6.

*RQ6: Which geographic differences can be seen in human-AI terminology?* We extracted country and continent from authors' affiliations using OpenAI's GPT-4o mini,<sup>19</sup> which is one of the most recent Large Language Models (LLMs). LLMs have the capability of including context into their analysis and offer intuitive interaction, making them a useful tool for text analysis (Rathje et al., 2024), where GPT-4o mini is particularly suitable for extracting searched for information, e.g., location details. In our data extraction process, we considered each country only once per publication if more than one author was affiliated with the respective country. Results were continuously cross-checked by one main researcher. The locations in combination with the associated subclusters per publication yield visualizations that allow for geographic analysis on country and continent level.

*Continent-level.* Figure 7a is based on the absolute numbers of publications per terminology subcluster and continent. The heatmap indicates pronounced research contribution in North America, followed by Europe and Asia. Focal points based on continents can be seen for “collaboration” and “interaction” in North America, Europe and Asia and “team” in North America and Europe. Human-AI research was sparsely covered in Australia, South America and Africa. This might be due to disadvantageous legal regulations (Jackson Bertón, 2021) or

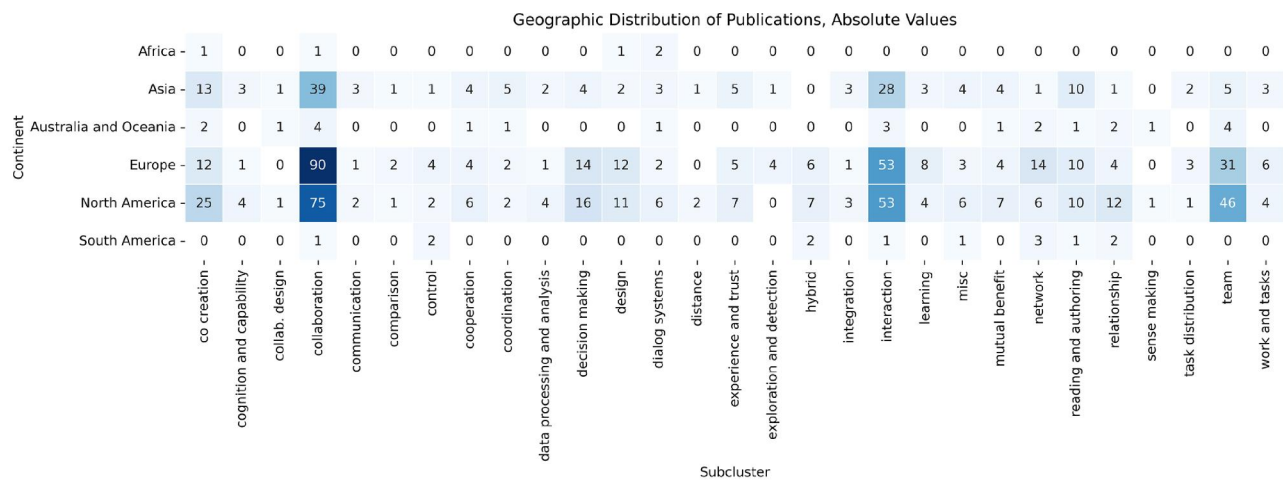
**Table 3.** Key authors in human-AI literature with contributions to up to 14 publications, considering *not* only first-authorship.

Author	Count	Affiliation	Publications
Nathan J. McNeese	14	Clemson University	(Canonica et al., 2020; Flathmann et al., 2021, 2023, 2024; Hauptman et al., 2023, 2024; Mallick et al., 2024; McNeese et al., 2021; Schelble et al., 2021, 2023, 2024; Zhang, McNeese, et al., 2021; Zhang, Duan, et al., 2023; Zhang, Flathmann, et al., 2024)
Beau G. Schelble	9	Clemson University	(Flathmann et al., 2021, 2023; Hauptman et al., 2023, 2024; McNeese et al., 2021; Schelble et al., 2021, 2023, 2024; Zhang, Flathmann, et al., 2024)
Vincent Aleven	8	Carnegie Mellon University	(Echeverria et al., 2020, 2023; Holstein et al., 2020; Holstein & Aleven, 2022; Karumbaiah et al., 2023; Thomas et al., 2024; Yang et al., 2021, 2023)
Christopher Flathmann	8	Clemson University	(Flathmann et al., 2021, 2023, 2024; Hauptman et al., 2024; Mallick et al., 2024; Schelble et al., 2021; Zhang, Duan, et al., 2023; Zhang, Flathmann, et al., 2024)
Kenneth Holstein	8	Carnegie Mellon University	(Echeverria et al., 2020; Gmeiner et al., 2024; Holstein et al., 2020, 2023; Holstein & Aleven, 2022; Kawakami et al., 2022; Morrison et al., 2023; Yang et al., 2023)
Mary Lou Maher	8	University of North Carolina at Charlotte	(Karimi et al., 2020; Kim, Maher, et al., 2021; Rezwana et al., 2021; Rezwana & Maher, 2023a, 2021, 2023c, 2023b, 2022)
António Correia	7	University of Jyväskylä, University of Nebraska at Omaha, INESC TEC and University of Trás-os-Montes e Alto Douro	(Correia, 2024; Correia et al., 2020, 2021, 2024, 2023; Correia & Lindley, 2022; Guimaraes et al., 2021)
Toby Jia-Jun Li	7	University of Notre Dame	(Gebreegziabher, Zhang, et al., 2023; Ning et al., 2024; Zhang, Ning, et al., 2023; Suh et al., 2024; Yang et al., 2022; Zhang, Xu, et al., 2022; Zhang, Gao, et al., 2023)
Jeba Rezwana	7	University of North Carolina at Charlotte	(Karimi et al., 2020; Rezwana et al., 2021; Rezwana & Maher, 2023a, 2021, 2023c, 2023b, 2022)
Casey Dugan	6	IBM Research	(Ashktorab et al., 2020, 2021, 2023; Brachman et al., 2022; Munyaka et al., 2023; Wang et al., 2019)
Niklas Kühl	6	University of Bayreuth	(Jakubik et al., 2023; Morrison et al., 2024; Schemmer et al., 2022; Schoeffer et al., 2024; Schemmer et al., 2023; Vössing et al., 2022)
Q. Vera Liao	6	Karlsruhe Institute of Technology	(Ashktorab et al., 2020; Chen, Liao, et al., 2023; Fan et al., 2022; Lai et al., 2022, 2023; Prabhudesai et al., 2023)
Besmira Nushi	6	Microsoft Research	(Amershi et al., 2019; Bansal et al., 2019a, 2019b; Fogliato et al., 2022; Inkpen et al., 2023; Peng et al., 2022)
Nikol Rummel	6	Ruhr-Universität Bochum	(Echeverria et al., 2020, 2023; Holstein et al., 2020; Karumbaiah et al., 2023; Yang et al., 2021, 2023)
Michael Vössing	6	Karlsruhe Institute of Technology	(Hemmer et al., 2022, 2023; Jakubik et al., 2023; Schemmer et al., 2022; Vössing et al., 2022; Westphal et al., 2023)
Rui Zhang	6	Clemson University	(Flathmann et al., 2021, 2024; Schelble et al., 2024; Zhang, McNeese, et al., 2021; Zhang, Duan, et al., 2023; Zhang, Flathmann, et al., 2024)
Zahra Ashktorab	5	IBM Research	(Ashktorab et al., 2020, 2021, 2023; Brachman et al., 2022; Munyaka et al., 2023)
Wen Duan	5	Clemson University	(Flathmann et al., 2024; Hauptman et al., 2024; Schelble et al., 2023; Zhang, Duan, et al., 2023; Zhang, Flathmann, et al., 2024)
Vanessa Echeverria	5	Carnegie Mellon University, Esc. Superior Politécnica del Litoral, Monash University	(Echeverria et al., 2020, 2023; Yan et al., 2024; Yang et al., 2021, 2023)
Eric Horvitz	5	Microsoft Research	(Amershi et al., 2019; Bansal et al., 2019a, 2019b; Fogliato et al., 2022; Segal et al., 2022)
Kori Inkpen	5	Microsoft Research	(Amershi et al., 2019; Fogliato et al., 2022; Inkpen, 2024; Inkpen et al., 2023; Peng et al., 2022)
Ece Kamar	5	Microsoft Research	(Bansal et al., 2019a, 2019b; Liu et al., 2020; Peng et al., 2022; Segal et al., 2022)
Qian Pan	5	IBM Research	(Ashktorab et al., 2020, 2021, 2023; Brachman et al., 2022; Munyaka et al., 2023)
Gerhard Satzger	5	Karlsruhe Institute of Technology	(Hemmer et al., 2022, 2023; Schemmer et al., 2023; Vössing et al., 2022; Westphal et al., 2023)
Zheng Zhang	5	University of Notre Dame	(Gebreegziabher, Zhang, et al., 2023; Ning et al., 2024; Zhang, Gao, et al., 2023; Zhang, Xu, et al., 2022; Zhang, Ning, et al., 2023)

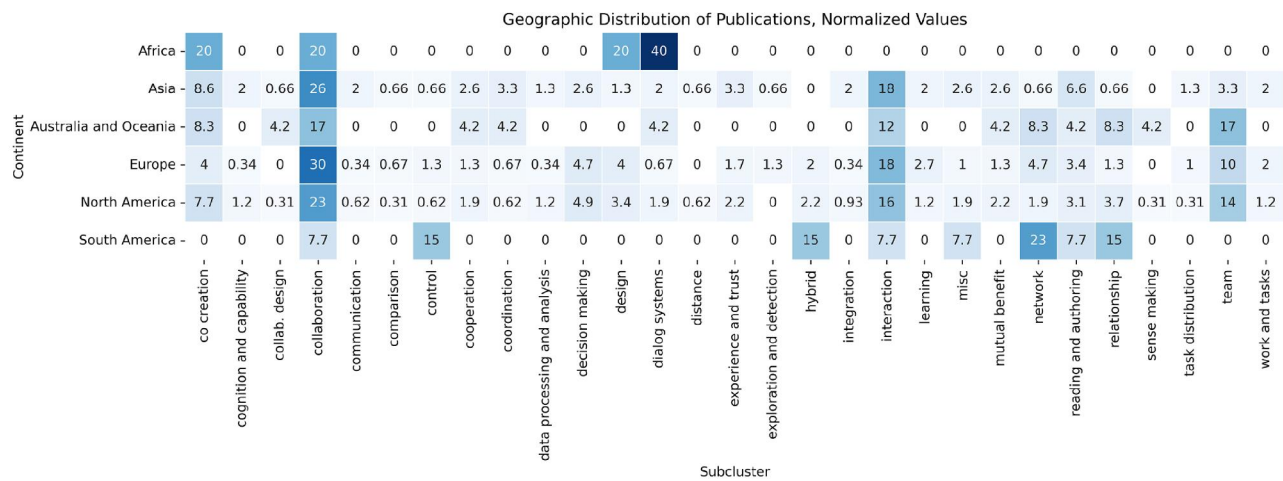
limited economic resources and necessary infrastructure (Kiemde & Kora, 2020). Further, the absolute numbers of human-AI publications are of course also affected by general aspects such as continent size, number of higher education and other research institutes there and similar. For instance, according to the uniRank directory,<sup>20</sup> there are currently 62 officially recognized higher-education institutions in Oceania (including Australia) versus 1,858 in North America or 2,706

in Europe. Additionally, as pointed out by Williams (who also states that “Australia does not yet have an artificial intelligence strategy or roadmap”; Williams, 2019, p. 111), the investment in research and development in general, differs for different nations (e.g., 0.4% of the GDP in Australia compared to 1.18% in South Korea or 0.75% in the US in 2015) (Williams, 2019).

Also, the discrepancies of human-AI research coverage in absolute numbers, do not fully allow for within-continent



(a) Heatmap based on absolute numbers of publications.



(b) Heatmap based on relative numbers normalized by overall number of publications per continent.

**Figure 7.** Geographic distribution of human-AI terminology on continent-level based on the subclusters found in human-AI literature.

analysis of research interests and terminology usage. For this reason, numbers in [Figure 7b](#) are normalized by the overall number of publications per continent to provide a more detailed view of research interests within continents. This visualization can be read line-wise and reveals focal points within continents that vanished in [Figure 7a](#). While collaboration, interaction and team subclusters still stand out in the normalized figure, research activity in South America and Africa does not necessarily seem to align with the main streams visible for other continents. For example, publications affiliated with South America most frequently concern “network”, “control”, “hybrid” and “relationship” subclusters and “dialog systems” is the most prominent subcluster for publications affiliated with Africa. Normalized values for the “team” subcluster are surprisingly low for Asia, while values for “co-creation” and “reading and authoring” are comparatively high. Europe and North America show similar focal areas with only slight deviations, e.g., higher “co-creation” and “relationship” values for North America and higher “collaboration” and “learning” values for Europe. Note that,

due to the sparse coverage of human-AI literature in Africa, Australia and South America, their focal points, e.g., on “hybrid” for South America, are strongly visible, while focal points stand out less strongly for continents with overall broad coverage.

*Country-level.* Subsequently refining the perspective on the global distribution, countries within continents may contribute to research to different degrees. Especially for continents that consist of a large number of individual countries, such as Europe, differences may be discovered by investigating the countries’ focal areas. [Figures A2\(a to f\)](#) in [Appendix A](#) show all countries within their respective continents with color intensities indicating their overall contribution in the respective subcluster.

## 5. Thematic analysis

This section extends our analyses by including the respective publications’ contents rather than just the presence of terms in their titles. According to Braun and Clarke, thematic



analysis is “a method for identifying, analysing and reporting patterns (themes) within data” (Braun & Clarke, 2006, p. 79), which, even though flexible in nature, commonly “involves the searching across a data set—[...]—to find repeated patterns of meaning” (Braun & Clarke, 2006, p. 86). In our analysis, we aim to find patterns in the conception, usage, perception and co-occurrence of specific terminology in a subset of publications based on terms that occurred at least three times in our Q1 data as described in Section 2.1.

### 5.1. Term conception and usage

The usage and conception of terminology can unveil hidden discrepancies, similarities and relationships. RQ7 focuses on different themes of conception and usage potentially stemming from a lack of clear definitions and awareness.

*RQ7: Which themes of term conception and usage consist in human-AI literature?* We extracted the usage and conception of different terms manually by either using explicit definitions stated in the text or by inferring them, e.g., from descriptions of application cases and study tasks the participants were confronted with. We briefly describe each of the terms and their usages and then summarize the findings based on the previously defined thematic clusters (see Section 3.4). The *Design* cluster did not contain any terms with at least three occurrences and is therefore not addressed in this section.

#### 5.1.1. Connection

In our corpus of selected literature, **Human-AI Teams** are seen as collaborative relationships between humans and AI, aiming for complementary performance, e.g., (Bansal et al., 2019b; Zhang, Lee, et al., 2022) and mutual benefit (Babbar et al., 2022). Zhang et al. more specifically describe human-AI teams as “an integrated unit where human and AI teammates, each with a significant degree of agency, coordinate and collaborate to complete team tasks with a shared goal” (Zhang, Flathmann, et al., 2024, p. 2) and state that for potentially superior performance in comparison to human-only teams “both a focus on the technical/task-focused contributions and the human-factors contributions of AI” (Zhang, Flathmann, et al., 2024, p. 2) are crucial. Challenges specific to human-AI teams include awareness (Endsley, 2023) and understanding of teammates (Munyaka et al., 2023), autonomy and interdependence (Ulfert et al., 2024) as well as individual and team trust (Georganta & Ulfert, 2024; Hou et al., 2025; Ulfert-Blank et al., 2023). Berretta et al. define **Human-AI Teaming** as “a process between one or more human(s) and one or more (partially) autonomous AI system(s) acting as team members with unique and complementary capabilities, who work interdependently toward a common goal” (Berretta, Tausch, Ontrup, et al., 2023, p. 23). Literature on human-AI teaming tends to focus on establishing functioning human-AI teams (Hauptman et al., 2023; McNeese et al., 2021) and factors that may enable or influence their effectiveness (Berretta, Tausch, Ontrup, et al.,

2023; Koehl & Vangsnæs, 2023; Milella et al., 2023). Authors describe the need for understanding and awareness, adaptivity and the importance of the AI system being a “real” member of the team rather than a tool, with expectations and standards applied similar to those in human teams (Berretta, Tausch, Ontrup, et al., 2023; Hauptman et al., 2023; McNeese et al., 2021; Schelble et al., 2024). Berretta et al. further point to *human-technology teaming* and *human-autonomy teaming* as related research fields, which we could also identify in Section 3.1. With **Human-AI Teamwork**, researchers investigate interactions and dynamics between human and AI teammates (Jorge et al., 2023; Mallick et al., 2024; Peng et al., 2022; Schechter et al., 2023) and what may be specific to human-AI rather than human-only teams (Schechter et al., 2023).

Kawakami et al. summarize **Human-AI Partnerships** as “configurations of humans and AI systems that can draw upon complementary strengths of each” (Kawakami et al., 2022, p. 1). Further, Xu et al. describe “a genuine human-AI partnership capable of mimicking the dynamic adaptability of humans” (Xu, Hong, et al., 2023, p. 1) and humans and AI as “fellow team members who can both reactively and proactively collaborate” (Xu, Hong, et al., 2023, p. 1). Partnerships may thus be collaborative relationships (Omidvar-Tehrani et al., 2024; Xu, Hong, et al., 2023; Weisz et al., 2021) with discussions including involvement, roles (Omidvar-Tehrani et al., 2024; Waefler & Schmid, 2020), acceptance and reliance (Kawakami et al., 2022; Nguyen et al., 2018; Weisz et al., 2021) and resulting design implications. A **Human-AI System** may broadly be a combination of humans and AI, described as an intertwined sociotechnical system (Naikar et al., 2023). Publications emphasize the importance of human focus in the design of AI interfaces and interactions (Correia & Lindley, 2022; Subramonyam et al., 2022). **Human-AI Complementarity** emphasizes superior performance that can only be reached by combining human and AI capabilities strategically. Publications focus on the optimal integration of human and AI contributions (Tan et al., 2022; Yang, Zhang, et al., 2024), impact factors (Steyvers et al., 2022) and the design and tuning of AI to complement the individual human’s capabilities (Holstein & Alevén, 2022; Inkpen et al., 2023). **Human-AI Symbiosis** may be similar to complementarity and collaboration at first glance, focusing on working together and aiming for AI to support rather than replace humans (Mahmud et al., 2024; Jarrahi, 2018). The distinctive feature of symbiosis appears to be the trigger of an advantageous situation (Bendoly et al., 2024; Ilapakurti et al., 2019; Vuppalapati et al., 2020) that enables humans to act upon. **Human-AI Synergy** may describe a holistic view on complementarity and human focus, taking affordances (Bao et al., 2023) and behavioral science (Van Rooy & Vaes, 2024) into account. Fabri et al. adopt a definition of **Human-AI Hybrids** as “combinations of capabilities of human agents and AI-enabled systems” (Fabri et al., 2023, p. 625). They highlight the importance of clear definitions and investigating human-AI hybrids as close interworking of humans and AI

from more than one perspective (Fabri et al., 2023), for which they develop a taxonomy including archetypes of human-AI hybrids ranging from automation to co-evolution. Fahse and Schmitt refer similarly to the concept while focusing on real-life settings (Fahse & Schmitt, 2023). Allred et al. describe a complementary human-AI hybrid that is superior to established techniques for author masking (Allred et al., 2020).

2021; Cabrera et al., 2023; Holstein et al., 2023; Schmidt & Biessmann, 2020). In conditional delegation, both humans and AI delegate decision tasks to the better suited collaboration partner for efficient use of the complementary capabilities (Lai et al., 2022). Integrating human knowledge in AI model development (Siirtola & Rönning, 2019) may reflect the AI communities' perspective of human-AI collaboration, where the goal is to improve model performance. Another stream of literature

#### Summary

The *Connection* cluster highlights the importance of human-centered approaches in human-AI relations. This is reflected by the relationship-focused perspective, investigating how connections between humans and AI should be designed and what may impact them. Forming teams or partnerships between humans and AI mostly aims for collaborative and complementary relationships, where human-AI teaming may be the process of establishing functioning human-AI teams and research concerning human-AI partnerships may even more focus on AI as a capable fellow team member. A holistic approach may be reflected in literature describing human-AI synergies, while in human-AI symbiosis leveraging human and AI knowledge to spark a symbiotic effect to help humans may be a different approach to human-centeredness.

#### 5.1.2. Working together

**Human-AI Interaction** addresses the characteristics of interaction with AI in comparison to conventional HCI (Amershi et al., 2019; Shin et al., 2019; Wienrich & Latoschik, 2021). Researchers investigate what makes interaction with AI special and which new challenges arise with it (Liu, 2021; Sundar, 2020; Yang et al., 2020), especially considering the uncertainty of the AI's outcome. While commonly the human is in the focus rather than technical aspects, discussions concerning human-AI interaction in our literature range from mere acceptance of an AI system and its decisions (Liu, 2021) to actually investigating the ways humans can interact with AI (Kim et al., 2023) and an overall shift from HCI to human-AI interaction. Crompton describes human-AI interaction in decision making, where “the human agent (re-)acts on the output of the AI, and the AI (re-)acts on the output of the human agent” (Crompton, 2021, p. 1). **Human-AI Collaboration** takes advantage of the complementary skills of both parties, i.e., humans' ability to use intuition and reason based on experience and AI's computational power. In human-AI literature, a range of applications are considered *collaborative* with different degrees of involvement and focus on enhancement of either party. Including an AI collaborator may facilitate human collaboration and educate human collaborators (Sharma et al., 2023; Wang et al., 2019) or reduce the required human effort. Collaboration in decision making frequently refers either to decision support systems or conditional delegation. In this context, it is noteworthy to mention *human-AI collaboration protocols* which specify “how human decision makers should interact with the machines that support them” (Cabitza et al., 2021, p. 2) and deal with the interaction process and questions such as when to present what (decision-related) information. For instance, the sequence of advice presentation (e.g., human-first vs. AI-first) can play an important role in the design of human-AI systems (Cabitza et al., 2023). In summary, decision support systems provide AI recommendations or advice to support humans in their final decision and therefore integrate additional knowledge (Bossen & Pine, 2023; Cabitza et al.,

investigates human-AI collaboration in exploratory applications, where the human provides guidance to approach a desired goal (Strobelt et al., 2022). Literature contains critical arguments towards the collaborative nature especially of decision support systems. Simple decision support systems do not include factors frequently considered essential to collaboration, such as reciprocity, equal contribution and learning from each other (Dellermann, Calma, et al., 2019). Several publications concerning human-AI collaboration discuss the importance of feedback, awareness of information available to the collaborator (Holstein et al., 2023) and the calibration of appropriate trust and reliance (Cabrera et al., 2023; Okamura & Yamada, 2020a). Despite the unresolved challenges, human-AI collaboration literature does show endeavors towards hybrid intelligence (Sowa et al., 2021). The term **Human-AI Collaborative Approach** is more frequently used for systems that are intended to perform or enable collaboration, not necessarily focusing on the process and team aspect of collaboration (Lee et al., 2021). In **Human-AI Co-Creation**, humans and generative AI aim to create or explore something new. Examples include, however may not be limited to, areas with a focus on creativity and personal expression, such as painting and music co-creation (Huang et al., 2020; Lyu et al., 2022). Even though intuition and expression as human abilities are difficult for AI to adopt or imitate, human creativity can be enhanced by including AI in the process of collaborative creation (Yu et al., 2022). This is specifically of interest in **Human-AI Co-Creativity**, which “involves humans and AI collaborating on a shared creative product” (Rezwana & Maher, 2023a, p. 62) and is being researched by Computational Creativity and HCI researchers (Kim, Maher, et al., 2021; Moruzzi & Margarido, 2024). Rather than creativity support (Rezwana & Maher, 2023a) or generative creativity (Kim, Maher, et al., 2021), human-AI co-creation reflects a collaborative approach of designing, making music (Rezwana & Maher, 2023a) or creating artwork together. The collaborative and uncertain nature of creating and creativity may shape the specific kind of interaction in human-AI co-creation and co-creativity. Publications using **Human-AI Co-Creative System** focus on the design and

dynamics in such collaborative relationships (Buschek et al., 2021; Rezwana & Maher, 2021, 2023b). Application cases of **Human-AI Cooperation** include the assignment of tasks to the better suited (human or AI) teammate for optimal performance (He et al., 2023; Salikutluk et al., 2023), cooperative games (Atkins et al., 2021; Le Guillou et al., 2023; Schelble et al., 2021) and decision making, where “human participants make their initial decision first, observe their teammate’s decision, and then make their final decision” (Zhang, Chong, et al., 2023, p. 2). Among other topics, researchers investigate trust (Okamura & Yamada, 2020b, Zhang, Chong, et al., 2023, Schelble et al., 2021), adaptive autonomy (Salikutluk et al., 2023) and mental models (He et al., 2023;

challenging barriers to taking advantage of AI in human decision-making” (Wang & Ding, 2024, p. 1). Common approaches to enhance transparency and therefore trust include explanations, however, researchers have noticed the importance of not only establishing, but maintaining trust: Zerick et al. highlight the importance of human-AI trust and specifically focus on recognizing and restoring trust once lost, stating that “by its nature, adoption of AI necessitates more than mere acceptance: it requires trust” (Zerick et al., 2024, p. 1). Further, Li et al. address trustworthiness of AI and human trust towards humans, automation and AI (Li, Wu, et al., 2024), proposing a framework of AI trust informed by psychological perspectives to trust.

#### Summary

The uncertainty of AI output seems to shape a different kind of interaction which poses new challenges in the design and development in comparison to conventional HCI research. AI and humans possess complementary strengths for a range of different tasks, which may enable and encourage collaboration to reach superior joint performance that could not be reached by either party alone. Complementarity and uncertainty are necessary for specific contexts, e.g., human-AI co-creation in art, as creativity requires uncertainty on the AI side.

Publications refer to a range of settings with different degrees of involvement and directions of support as collaborative. Two main streams of research describing “human-AI collaboration” are related to decision support systems and conditional delegation, which differ from each other in the partition of decisions. In addition, human-AI collaboration includes facilitation and mediation of human collaboration, education and improvement of human capabilities, joint problem solving, guided joint exploration and improvement of AI performance. This wide range of settings considered “collaborative” calls for a more thorough investigation of the definition of collaboration in human-AI relations to avoid jingle fallacies. This is emphasized by arguments in existing literature regarding the collaborative nature of, e.g., decision support systems. A potential risk for jangle fallacies can be seen in some instances of similar use of collaboration and cooperation in human-AI literature.

Le Guillou et al., 2023) in human-AI cooperation. In **Human-AI Communication**, Pan et al. and Brandtzaeg et al. investigate agency and perception of conversational AI systems (e.g., ChatGPT, communicating in human language) in human-AI communication (Pan et al., 2024, Brandtzaeg et al., 2022). Koçak et al. aim to account for semantic ambiguities different humans may bring into human-AI communication, using potential ambiguities in communication codes in an advantageous manner (Koçak et al., 2022). **Zero-Shot Human-AI Coordination** aims “to develop an agent capable of collaborating with humans without relying on human data” (Yan et al., 2023, p. 1). Zero-shot approaches are relevant to various application cases where adaptation to humans is necessary, yet the collection and integration of human data in the training process is costly, such as conversational systems, robotics, self-driving vehicles and gaming (Lou et al., 2023; Yan et al., 2023; Zhao, Song, et al., 2023). Human data is therefore simulated by agents in approaches such as self-play or population-based methods to train RL models (Yan et al., 2023; Zhao, Song, et al., 2023; Lou et al., 2023). **Human-AI Work** concerns the impact of the introduction of AI in work contexts on work practices, dynamics and workers (Berretta, Tausch, Peifer, et al., 2023; Ruissalo, 2024) as well as configurations of humans and AI working together and technology adoption, e.g., in agricultural settings (Hüllmann et al., 2023). A lack of **Human-AI Trust** commonly stems from the black-box nature of AI models (Lou & Wei, 2023; Wang & Ding, 2024), making it difficult for humans to appropriately calibrate to them. For example, Wang and Ding state that “the lack of trust in algorithms sealed in the “black box” is one of the most

#### 5.1.3. Applications

**Human-AI Decision Making** refers to AI assisting the human in the decision making process. Commonly, the human decision maker is provided with AI recommendations or predictions and can then either accept or reject them for the final decision. The noticeably strong focus on explanations (Jakubik et al., 2023; Morrison et al., 2024; Schemmer et al., 2022; Schoeffer et al., 2024) shows an aim for supporting the human decision maker in the decision whether or not to rely on the AI recommendation. Publications on human-AI decision making mention various high-stakes application domains, such as medicine, law and finance. Several publications additionally describe an aim for complementarity. Puranam refers to **Human-AI Collaborative Decision Making** as a setting where “humans and AI algorithms through some form of collaboration, together produce a decision that is implemented by a third party” (Puranam, 2021, p. 75). While the specific terminology may not necessarily reflect a strong difference between decision making and *collaborative* decision making in this case (Cai et al., 2019), Wang et al. emphasize the importance of restoring trust to enable collaboration in human-AI decision making and aim to address explanations and autonomy in collaborative decision making (Wang, Yuan, et al., 2024). Authors further integrate human knowledge in reinforcement learning processes (Mentzas et al., 2021) or focus on the onboarding and introduction to AI assistants (Cai et al., 2019). In **Human-AI Collaborative Writing**, textual content is created jointly by humans and AI. Collaboratively created content is commonly influenced by prompts to retrieve LLM outputs, but also by human the human decision of whether or not to adopt the generated text or to possibly adapt

it according to the individual needs (Richburg et al., 2024). Richburg et al. specifically focus on authorship analysis for collaboratively generated content, which becomes increasingly challenging with interdependent contributions of both parties (Richburg et al., 2024). Further, authors investigate LLMs' capabilities in different collaborative writing contexts (Lee, Liang, et al., 2022) and the practical impact of contemporary collaborative writing approaches, i.e., text generation with LLMs, on professional writing (Knowles, 2022). In **Human-AI Pair Programming**, "the practice of two programmers working together on the same task using a single computer, keyboard, and mouse" (Ma, Wu, et al., 2023, p. 1) is applied to humans and AI as programming partners. Authors investigate the differences and potentials of human-AI pair programming in comparison to the conventional setting of human pair programming (Ma, Wu, et al., 2023) and aim to address the common black-box problem in (AI) model development by providing AI advice and visualizations to the human developer (Jiang, Ahmadon, et al., 2024; Jiang, Bin Ahmadon, et al., 2023; Zhang, Wei, et al., 2022).

#### Summary

Human-AI decision making by itself appears to be a well-defined concept. There is a particularly strong focus on tuning appropriate reliance on the AI's recommendations, but also on complementarity between humans and AI to surpass individual performance of each. The *Applications* cluster further shows a surge in research interest in human-AI collaborative writing, which poses challenges concerning the differentiation of authorship of jointly generated content and the adaptation to and impact on humans. In human-AI pair programming, AI is seen as a partner facilitating programming of, e.g., complex models.

## 5.2. Co-occurrence

Shared discussions and research interests can indicate conceptual relationships between terms, e.g., communication may be relevant in the context of teaming. With RQ8, we investigate such conceptual relationships and semantic associations.

*RQ8: Which semantic associations can be found in human-AI terminology?* We performed a co-occurrence analysis on document level to find conceptually related terms. Such an analysis is suitable for investigating term-specific semantic associations and supports the inference of conceptual relations between the different terms in the same document. In our case, rather general, more prominent terms (e.g., "collaboration" or "interaction") may have more co-occurrences with other terms than those tailored to one specific problem (e.g., "trustworthy human-AI collaboration"). Thus, our analysis is focused on the most prominent human-AI terms with more than two occurrences as described in Section 5, as including all proved to result in a largely "empty" co-occurrence matrix in preliminary implementations. Figure 8 shows the co-occurrence of the most prominent terms, with connection strength between terms depicted by color intensity.

For the analysis, all co-occurring terms were automatically extracted from all publications in a machine-readable PDF format using a Python script. A co-occurrence was considered if one term occurred with another term in the same file but not with itself. Furthermore, multiple occurrences of the same terms were not quantified, resembling a Boolean data type or nominal scale. The list of terms extracted from Q1 (see Section 2.1) served as a basis to be searched for in the papers.

We harmonized both the PDF files and the set of search terms as described in Section 2.1 and Section 3.3 and analyzed the data based on the connection strength shown in Figure 8.

Strong connections among the most popular terms suggest that they do not necessarily represent different research directions but build a strongly intertwined core around "collaboration", "interaction" and "team" in human-AI research. This core focus possibly indicates the need for intuitive interaction between humans and AI to enable collaboration and is also visible in combination with several other terms, such as HAI partnership, HAI decision making, HAI collab. decision making, HAI system and HAI symbiosis. A focus on complementarity is visible for HAI collaboration, HAI team and HAI decision making. HAI collab. decision making, while interpreted similarly to HAI decision making in Section 5.1, seems to be discussed as a "collaborative approach", possibly enabling collaboration in human-AI decision making. With terms related to joint creation and creativity, e.g., "HAI co creation", "HAI co crea-

tivity" and "HAI co creative system", concepts otherwise relevant to human-AI relations are hardly discussed: They show weak or no connections to "HAI trust", "HAI complementarity" or "HAI cooperation". Complementarity though is frequently discussed in combination with "HAI collaboration", "HAI interaction" and "HAI decision making", reflecting the use of complementary strengths for optimal *performance*, which may not be the goal in co-creative settings. Some terms show overall weaker connections. This may suggest research performed separately from others, specificity of a term (e.g., "HAI pair programming" may not be discussed frequently as a common part of human-AI relations, but rather reflect a specific approach or application case) or, in contrast, a concept commonly discussed without the need for an explicit human-AI term. For example, *trust* may be relevant to many discussions in human-AI relations, yet, authors may not explicitly refer to it as "human-AI trust" in publications concerning human-AI relations. Investigating such cases may require a more thorough, focused co-occurrence analysis including relevant terms and descriptions of specific concepts rather than our overview of human-AI terminology.

## 6. Discussion

With our scoping review, we aimed at mapping the landscape of terminology used in scientific human-AI literature to provide a broad overview of the usage and consistency of terms, discussed topics, and the evolvement over time. In the following, we discuss the implications and limitations of our research and identify our main contributions.



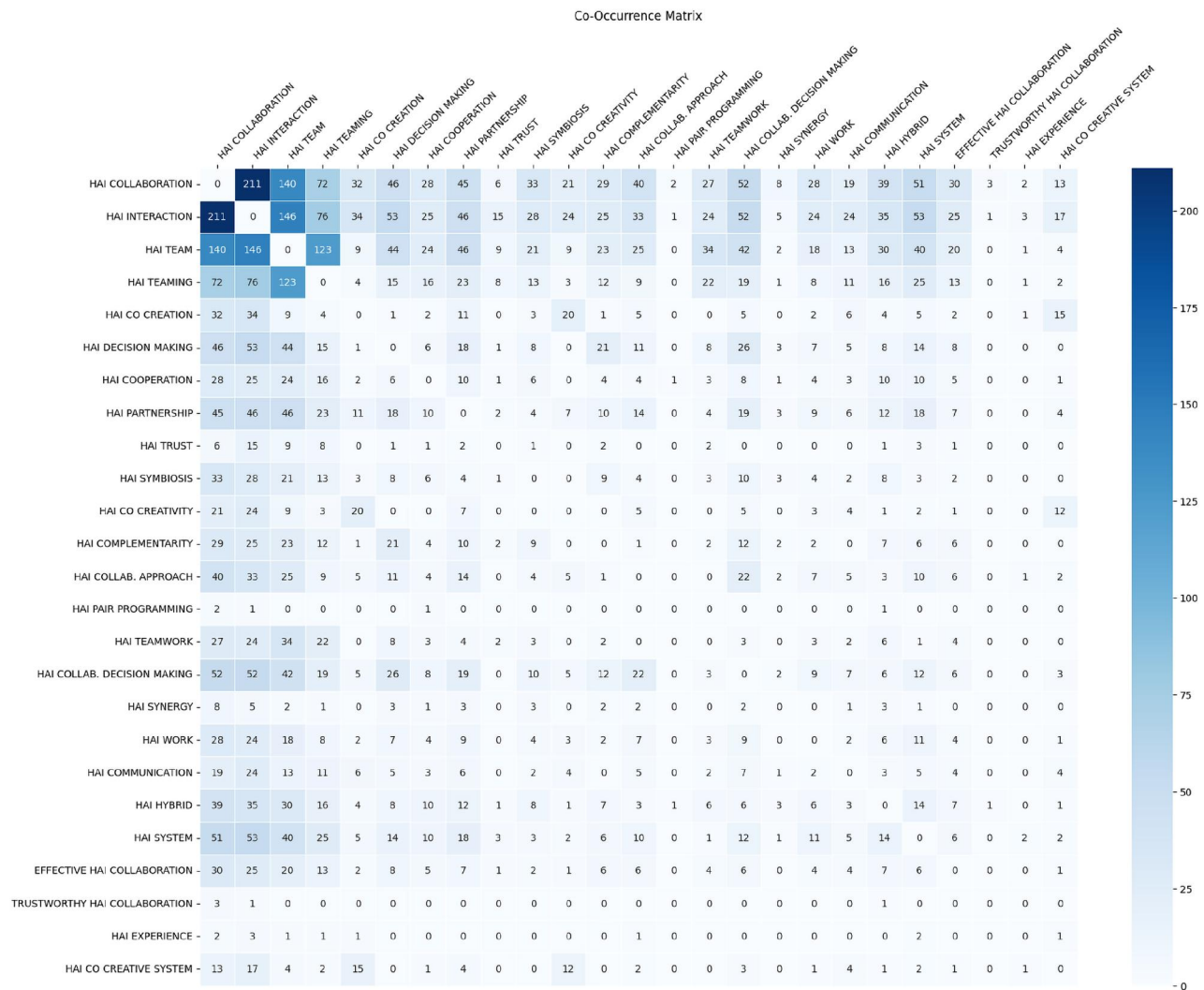


Figure 8. Co-Occurrence matrix of pairs of most popular human-AI terms.

### 6.1. Implications and contributions

As explained in Section 1, the rapid advancements in AI research in general as well as a shift of its focus towards human-centered AI hold the risk of emerging two-sided inconsistencies (e.g., ambiguities) in the terminology used to characterize relations between humans and AI.

First, as shown in Table 1, we extracted a set of different alternative terms for “AI” from the literature. This is in line with the findings of Langer et al., (2022) and (Graziani et al., 2023), investigating terms used to refer to AI systems. Both Langer et al. (2022) as well as Graziani et al. (2023) already found significant differences in the perception of and expectations towards AI systems depending on the wording. Awareness of the variety of terms and their usage and conception is therefore crucial to identify possible inconsistencies in terminology and facilitate purposeful selection of appropriate terms. Besides the appropriate calibration of individuals’ expectations and trust towards AI systems, inconsistent terminology holds risk for societal implications: In legal contexts, precise definition of individual terms may be critical to ensure fair jurisdiction. For instance, in the European Union region, the General Data

Protection Regulation (GDPR),<sup>21</sup> regulates how personal data of individuals may be processed and transferred. According to the GDPR, humans are entitled to human judgment in automated decisions, requiring the terminology to be clear on human involvement and authority in the decision-making process. In high-stakes settings, e.g., autonomous vehicles or medical applications of AI, liability of human vs. AI may be decided based on the term precisely describing the situation. Further, inconsistent terminology may impede complementary research especially in interdisciplinary fields.

Our findings confirm and extend Langer et al.’s and Graziani et al.’s observations: as our review indicates, human-AI terminology largely appears to be influenced by the development of a new shape of interaction. Contrary to conventional systems, AI outputs hold uncertainty which leads to potentially unpredictable results. A large proportion of literature therefore focuses on the peculiarities of interaction and the collaborative, complementary relationship of humans and AI. Awareness of trending and emerging terms, such as “human-AI collaboration” or “human-AI symbiosis”, supports the consistent use of terminology and development of conventions, while clear definitions are yet to be made.

To further support clear terminology in human-AI relations, existing standard definitions, e.g., in ISO/IEC 22989:2022 or the European AI Act, may provide a solid base for future research. Researchers may leverage standard definitions and focus on contributions, conceptions and influences of different domains, such as Computer Science including HCI and AI, Psychology, Sociology and Linguistics, to find common concepts or even important differences. With respect to trends and newly emerging terminology in human-AI relations, future research may systematically explore the origin and development of individual terms in scientific literature. This may reveal relatedness of terms across disciplines, or between newly emerging and already established terms. Complementarily, we argue that collaborative approaches towards establishing precise terminology may be particularly suitable for interdisciplinary research. Towards this end, we, on one hand, suggest a systematic integration of the terminological discussion in the premier scientific venues of the relevant communities – e.g., in the form of dedicated workshops at conferences such as ACM CHI or ACM IUI (where, typically, the HCI and AI audience meets). On the other hand, we suggest dedicated studies for the development and evaluation of a shared terminology across scientific communities. One suitable method for such studies could be inspired by the Delphi technique, which has been originally conceptualized as a systematic method for eliciting expert opinion. While various authors reflected overly critically on the original Delphi method, pointing out problematic aspects such as “unaccountable sampling” of “experts”, “[s]eriously confusing aggregations of raw opinion with systematic prediction”, “capitalizing on forced consensus based on group suggestion”, or “denigrating group and face-to-face discussion” (Sackman, 1974, p. 69, 70), or “complicated facilitator tasks”, “lack of real-time presentation of results” or “difficulties in tracking progress over time” (Gnatzy et al., 2011, p. 1), methodologically revised approaches aim to address the weaknesses of the conventional Delphi method while preserving its potentials to establish consensus of a particular topic among a group of experts (Turoff, 1970). Related to our use case on the establishment of a shared terminology within and across scientific communities, Delphi studies have, also in recent years, been successfully applied in similar endeavors. For instance, Schapira et al. in Schapira et al. (2020) describe a “modified Delphi process” for seeking consensus on the terminology of value-based transformation of health care. Other recent examples on endeavors for standardization of terminology in the health sector can be found in Denman et al., (2021) and Taze et al. (2022). Examples for Delphi studies in the broader fields of Computer Science and HCI can be found in Danial-Saad et al. (2013), where Danial-Saad et al. describe establishment of an ontology for assistive technology, in Parekh et al. (2018), where Parekh et al. identify core concepts of cybersecurity, or in Dawood et al. (2021) where Dawood et al. aim to establish a unified criteria model for usability evaluation in the context of open source software.

Furthermore, conjunctive terms used to describe human-AI relations are ambiguous in the opposite sense. The excessive use of trending terms, e.g., “collaboration” or “co-creation”

indicates either a rapid increase in research interest or term ambiguity (or both). The analysis of our comprehensive corpus of literature actually revealed considerable disparities in the use of specific terms (cf. Section 5.1 and RQ7), a trend which seems to persist in literature beyond the scope of our review – just lately, Sarkar (Sarkar, 2023) complained about excessive use of “human-ai collaboration” in recent scientific literature. For instance, in Gebreegziabher, Zhang, et al. (2023), “collaboration” between humans and AI is used to refer to a scenario in which an AI system and a human actually interact in a closely interwoven way (where, however, it remains the human who makes the decisions) to solve qualitative coding tasks, in Kuang et al. (2023), “collaboration” describes the interaction with a conversational AI in a Q & A style in the domain of UX evaluation, and in Xu, Lien, et al. (2023), “collaboration” is used to refer to AI assistance in annotation tasks. Additionally, it is remarkable that most of the recent literature on human-AI relations does not provide an exact definition of what is understood by e.g., “collaboration”.

Further, whereas the terms chosen for our review were defined to explicitly include “human” and “AI”, there are also terms containing only one of these words while implicitly considering the other party (e.g., “AI-assisted”, “AI-enhanced”, or “AI-supported”). While these terms often implicitly include humans, we assume that the integration of the second party involved can be seen as more single-sided and unbalanced or might be absent at all (e.g., in AI-enhanced computer systems). The *diversity in degrees of involvement* may range from mostly human- to mostly AI-sided involvement, with “collaboration” integrating both parties to a similar extent. Different degrees of involvement may shift roles and raise questions concerning autonomy, responsibility and ethics within the human-AI relationship. Subsequent targeted literature reviews could determine the differentiation and possibly provide a taxonomy systematically capturing the *different degrees of human-AI involvement*.

Our geographic analysis revealed that contributions mostly stem from countries associated with WEIRD (Western, Educated, Industrialized, Rich, Democratic) societies (Henrich et al., 2010). In line with this, Bol et al. highlight the higher prevalence of scientific journals in North America and Europe compared to the Global South and state that “Global North journals are often associated with international and global-level prestige, while Global South journals are presumed to be local, national or regional in scope” (Bol et al., 2023, p. 1). Legal regulations (Jackson Bertón, 2021) and limited economic resources (Kiemde & Kora, 2020) may contribute to this geographic disparity, causing different perspectives of underrepresented populations to remain unconsidered in the research and terminology of human-AI relations. The academic disadvantage of geographical regions, such as the Global South, may be counteracted by conscious citation of respective work or co-publishing of Global North and Global South publishing spaces to reach greater audiences (Bol et al., 2023). Bol et al. further discuss the potential advantage of decentralized editorial boards and journal indexing to support geographic equality in academic publishing (Bol et al., 2023). Future visions of a culturally

more inclusive human-AI research community may offer diverse perspectives more representative of the world's population.

*Our main contributions can be summarized as follows.* With this scoping review, we provided a *comprehensive overview of the terminology* used in scientific human-AI literature. Our results offer insights into *thematic clusters* and capture the *changing nature of human-AI relations over time* (e.g., from AI as a tool to AI as a team member). Analyses with different focal points provide a *general overview of the research field* while *enabling researchers to find specific literature*. Thematic analyses consider not only the choice of terminology, but also differences in conception and usage and the consequent co-occurrence with other terms. We strongly aim to contribute to the *harmonization of human-AI terminology* and facilitate the establishment of *more precise definitions* of prominent terms in the literature. This is of utmost importance as, according to Langer et al. (2022), consistent and precise terminology does not only impact human perception of and expectation towards AI systems, it also enhances the robustness and replicability of research findings. Our review further intends to *facilitate future research across domains and communities*. To this end, we aim to *raise awareness of research* but also *terminology used* in complementary or contrasting fields. This, according to our observation, is imperative because the recent surge of scientific activities around human-AI relations has clearly revealed that currently, there is a lack of established terminology across domains, but also continents and countries. This gap is further continuously amplified by intra-domain reinforcement (e.g., through names of workshops or newly established conferences).

## 6.2. Limitations

In the following, we summarize the main limitations inherent to our scoping review.

*Selection of human-AI terms.* Our review relies on a certain set of keywords included throughout Q1 to Q3. Even though we systematically researched alternative terms for both “human” and “AI”, we acknowledge that the selection might still not be exhaustive. For instance, Hirzle et al. (2023) and Langer et al. (2022) provide more extensive collections of alternative AI terms and keywords than those listed in Table 1. Examples include adjectives such as “supervised”, “generative” or “intelligent”, and terms for specific applications, such as “reasoning”, “recognition” and “segmentation” (Hirzle et al., 2023). While combinations of these may capture a wider range of human-AI literature, they oftentimes focus on specific applications or leave room for ambiguous interpretation, depending on the chosen combination. Langer et al.’s list of AI terms in use includes “algorithm”, “computer” and “robot”, which are also considered in our review. Further suggested terms comprise “decision support system”, “automated system”, “technical system” and “computer program” (Langer et al., 2022). While not explicitly present in our set of keywords, these terms are semantically covered by “system” and “computer”

in Q2 and Q3 of our review. Additional unconsidered terms mentioned by Langer et al., (2022) include “machine learning” and “sophisticated statistical models”. We are aware that our systematic approach to data collection based on term composition patterns may lead to the underrepresentation of relevant discussions with terminology diverging from the defined pattern. For example, Matamoros et al. only slightly diverge from our defined pattern by specifying a particular group of humans in “Teachers-AI Collaboration” (Matamoros et al., 2021). Their publication is therefore not included in our review, even though its investigation of educational recommender systems may be a highly relevant application case of human-AI collaboration. Further, Knijnenburg et al. discuss interaction methods for recommender systems (Knijnenburg et al., 2011), which one may clearly consider an application case of human-AI relations. Their publication’s title however does not state a specific human-AI term according to our defined pattern and is therefore not represented in our work. While we could not consider terminology specific to recommender systems, literature was included if it contained a, to our definition, valid human-AI term, e.g., in “Towards the design of user-centric strategy recommendation systems for collaborative Human-AI tasks” (Dodeja et al., 2024). Further, research communities such as IUI and Affective Computing are heavily engaged with human-centered approaches of AI. The relation in this case may be more implicit with a strong focus on adaptability derived from, e.g., the context and emotional state of the human, not necessarily reflecting a two-sided relation with equal consideration of both sides. This may be reflected in the terminology and thus, despite potentially containing highly relevant topics of human-AI relation, these research fields may be underrepresented in our work.

Moreover, for the analyses in Section 5, we only considered terms with at least three occurrences, and for popular terms, we selected only five publications per year. While we chose this sampling method as it represents the data well, it leaves out some publications that may include different conceptions, interpretations and co-occurrences.

We showed that terminology does not appear to be settled, seems to be partly volatile (see, e.g., the dynamic development reflected in Figure 3) and some terms have entirely fallen out of favor (e.g., “man” to mean humanity, which we, however, intentionally included to not omit older publications, such as Licklider’s work). As argued above, the emergence of new terms may not immediately be reflected in terms being used prominently in publications’ titles. While we focused on established terminology in our thematic analysis to capture the conception and underlying discussions of particularly *prior* and *recently prominent* terms, *future* studies focused on newly emerging terminology could highlight the evolvement of human-AI term usage beyond publications’ titles and investigate particularly origin and relatedness to established concepts.

*Considered combinations.* We did not include terms indicating *unbalanced involvement* of humans and AI (e.g., “AI-assisted human labeling”) or ambiguous terms that potentially



refer to other parties than humans or AI, or include only one party, e.g., “ai-enhanced software”. The combination of “human” and “AI” in close proximity within a term ensured less ambiguous results. Further analyses concerning all combinations of human and AI relations, including those that only implicitly include one (e.g., “AI-enhanced learning”, “AI-guided navigation”) or both (e.g., “collaborative intelligence”) of the two parties, can however add further value and broaden the view of the field.

*Depth of content-wise insights.* Following the goals of a scoping review, we aimed for a broad overview rather than an in-depth content-wise analysis. We performed thematic analyses to complement our findings based on the terminology, we, however, consider it an interesting part of future work to perform a subsequent systematic literature review to gain further insights into the associated content discussed in the human-AI literature. This subsequent review should be narrowed to specific parts of the field identified in this article, such as “collaboration”, “interaction” or “communication” among humans and AI.

*Database selection.* We purposefully selected databases to represent the primary context of human-AI relations in Computer Science (including, e.g., HCI research), while at the same time considering the interdisciplinarity of human-AI relations. Thus, we selected Scopus as an interdisciplinary primary database and further ACM Digital Library and IEEE Xplore as specialized supplementary databases [205, 206]. This selection provides a broad interdisciplinary inclusion of literature with focus on highly relevant areas given the specific context, however, we are aware that the strong focus on Computer Science and Engineering may undermine perspectives of further relevant research fields. Despite the relevance of diverse research fields to human-AI relations, we decided against the further inclusion of highly specialized databases as they did not yield sufficient amounts of relevant data for our specific analysis of human-AI terminology due to their narrow scope (Gusenbauer, 2022) and limited full-text availability in our preliminary searches. More in-depth content-wise analyses may however require the inclusion of further specialized databases, e.g., focusing on Social Sciences and Psychology, to holistically capture the nature of human-AI relations and potential societal impacts.

## 7. Summary and conclusion

In this article, we first analyzed the *historical development* (Section 3.1) and *term composition patterns* (Section 3.2), including alternative terms for “human” and “AI” leading to the current human-AI terminology. We then provided a *general overview of the terminology* (Section 3.3) present in our Q1 data, derived four *thematic clusters* with 30 subclusters and the meaning of terms within them (Section 3.4). Further, we identified *key authors* and the most *influential publications* in Sections 4.1 and 4.2 and described the *geographic distribution* of terms to refer to human-AI relations by researchers all over the world (Section 4.3). Finally, we investigated the *conception and interpretation* of terms in

human-AI literature (Section 5.1) and *co-occurrences* of specific terms (Section 5.2).

Our analysis revealed that the rapid advancement of AI and shift towards HCAI spiked research interest in a newly shaped kind of interaction different from conventional HCI. This led to the emergence of a variety of terms to describe collaborative relationships and efforts toward seamless integration of humans and AI with a lack of conventions and precise definitions. We could identify a large pool of terms relevant across domains and communities and investigated their conception and usage, where we could identify ambiguities in the evolving terminology. We further backed our findings with additional analyses for a comprehensive overview of the historical and current terminology in human and AI relations to provide a profound basis for future cross-domain research activities. While arguing for the development of terminological conventions in scientific literature, the rapid evolvement of AI technology and its terminology may limit the longevity of our own work. While longevity concerning the frequently discussed *publish-or-perish* mentality (Van Dalen & Henkens, 2012) and the limited lifespan of publications frequently poses challenges to researchers, we are confronted with obsolescence of research findings due to terminology evolvement. Though, we aim to capture the variety of terminology and advocate for its clear definition *at the present time*.

In conclusion, our scoping review opens a range of research questions to be further investigated. In our own future work, we foremost aim at analyzing in depth the concept of “human-AI collaboration”, establishing not only a profound definition but also a global and cross-domain taxonomy of prerequisites, components and characteristics.

## Notes

1. <https://artificialintelligenceact.eu/article/3/>, last access: 2024-10-13.
2. <https://www.iso.org/standard/74296.html>, last access: 2024-10-14.
3. <https://www.oecd.org/en.html>, last access: 2024-10-14.
4. <https://oecd.ai/en/wonk/definition>, last access: 2024-10-14.
5. <https://dl.acm.org/>, last access: 2024-10-12.
6. <https://www.scopus.com/>, last access: 2024-10-12.
7. <https://ieeexplore.ieee.org/>, last access: 2024-10-12.
8. We also experimented with “Artificial Intelligence” but found a significantly lower number of results (1,450 for the query using “AI” vs. 175 for “Artificial Intelligence”).
9. <https://www.researchgate.net/>.
10. Please keep in mind that we explicitly did not restrict our review to publications after a certain publication date.
11. <https://www.merriam-webster.com/>.
12. <https://www.powerthesaurus.org/>.
13. <https://digital-strategy.ec.europa.eu/en/library/eu-us-terminology-and-taxonomy-artificial-intelligence>.
14. <https://www.powerthesaurus.org/>.
15. <https://www.deepl.com/translator>.
16. By “man” we do not specifically refer to male persons but to any persons in general (especially older literature regularly uses it to mean “mankind”). To ensure inclusiveness we ran a test search with “woman” as alternative *human* term which however did not yield any results.
17. 2024 data is only available until September 2024, we however expect an ongoing development to be likely.



18. <https://serpapi.com/google-scholar-api>.
19. <https://platform.openai.com/docs/models/gpt-4o-mini>.
20. <https://www.4icu.org/>.
21. <https://eur-lex.europa.eu/eli/reg/2016/679/oj>, last access: 2024-12-16.

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## References

- Abbass, H. A., Petraki, E., & Hunjet, R. (2022). JSwarm: A jingulu-inspired human-AI-teaming language for context-aware swarm guidance. *Frontiers in Physics*, 10, 1–14. <https://doi.org/10.3389/fphy.2022.944064>
- Abedin, B., Meske, C., Junglas, I., Rabhi, F., & Motahari-Nezhad, H. R. (2022). Designing and managing human-AI interactions. *Information Systems Frontiers*, 24(3), 691–697. <https://doi.org/10.1007/s10796-022-10313-1>
- Adam, M., Diebel, C., Goutier, M., & Benlian, A. (2024). Navigating autonomy and control in human-AI delegation: User responses to technology- versus user-invoked task allocation. *Decision Support Systems*, 180, 114193. <https://doi.org/10.1016/j.dss.2024.114193>
- Adan, O., & Houben, S. (2023). CollEagle; Tangible human-AI interaction for collocated collaboration. In P. Lukowicz, S. Mayer, J. Koch, J. Shawe-Taylor, & I. Tiddi (Eds.), *Proceedings of the Second International Conference on Hybrid Human-Machine Intelligence* (pp. 416–418). Frontiers Artificial Intelligence and Applications, Vol. 368. IOS Press. <https://doi.org/10.3233/FAIA230115>
- Agarwal, O. (2024). MS slide designer: A study on human-AI collaboration for content creation. In *Proceedings of the 16th Conference on Creativity & Cognition (C&C '24)* (pp. 499–503). Association for Computing Machinery. <https://doi.org/10.1145/3635636.3664259>
- Ahn, J., Kim, J., & Sung, Y. (2024). The role of perceived freewill in crises of human-AI interaction: The mediating role of ethical responsibility of AI. *International Journal of Advertising*, 43(5), 847–873. <https://doi.org/10.1080/02650487.2023.2299563>
- Akintunde, M., Young, V., Yazdanpanah, V., Salehi Fathabadi, A., Leonard, P., Butler, M., & Moreau, L. (2023). Verifiably safe and trusted human-AI systems: A socio-technical perspective. In *Proceedings of the First International Symposium on Trustworthy Autonomous Systems (TAS '23)* (pp. 1–6). Association for Computing Machinery. <https://doi.org/10.1145/3597512.3599719>
- Al, P. (2023). (E)-Trust and its function: Why we shouldn't apply trust and trustworthiness to human-AI relations. *Journal of Applied Philosophy*, 40(1), 95–108. <https://doi.org/10.1111/japp.12613>
- Ala-Luopa, S., Koivunen, S., Olsson, T., & Väänänen, K. (2024). Considerations on human-AI collaboration in knowledge work – Recruitment experts' needs and expectations. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (pp. 197–206). IEEE Computer Society.
- Allen, R. A., White, G. R. T., Clement, C. E., Alexander, P., & Samuel, A. (2022). Servants and masters: An activity theory investigation of human-AI roles in the performance of work. *Strategic Change*, 31(6), 581–590. <https://doi.org/10.1002/jsc.2530>
- Allred, J., Packer, S., Dozier, G., Aykent, S., Richardson, A., & King, M. C. (2020). Towards a human-AI hybrid for adversarial authorship. In *Conference Proceeding IEEE Southeastcon* (pp. 1–8), Vol. 2020–March. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/SoutheastCon44009.2020.9249682>
- Alon-Barkat, S., & Busuioc, M. (2023). Human-AI interactions in public sector decision making: “Automation bias” and “selective adherence” to algorithmic advice. *Journal of Public Administration Research and Theory*, 33(1), 153–169. <https://doi.org/10.1093/jopart/ruac007>
- Amershi, S., Weld, D., Vorvoreanu, M., Fournery, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., & Horvitz, E. (2019). Guidelines for Human-AI Interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)* (pp. 1–13). Association for Computing Machinery. <https://doi.org/10.1145/3290605.3300233>
- Amresh, A., Cooke, N., & Fouse, A. (2023). A minecraft based simulated task environment for human AI teaming. In *Proceedings of the 23rd ACM International Conference on Intelligent Virtual Agents (IVA '23)* (pp. 1–3). Association for Computing Machinery. <https://doi.org/10.1145/3570945.3607305>
- Anderson, A., Guevara, J. N., Moussaoui, F., Li, T., Vorvoreanu, M., & Burnett, M. (2024). Measuring user experience inclusivity in human-AI interaction via five user problem-solving styles. *ACM Transactions on Interactive Intelligent Systems*, 14(3), 1–90. <https://doi.org/10.1145/3663740>
- Anderson, C. (2006). *The long tail: Why the future of business is selling less of more*. (American first edition ed.). Hyperion.
- Andre, F., Fortner, P., Aurich, M., Seitz, S., Jatsch, A.-K., Schöbinger, M., Wels, M., Kraus, M., Gülsün, M. A., Frey, N., Sommer, A., Görich, J., & Buss, S. J. (2023). Human AI teaming for coronary CT angiography assessment: Impact on imaging workflow and diagnostic accuracy. *Diagnostics*, 13(23), 3574. <https://doi.org/10.3390/diagnostics13233574>
- Andrews, R. W., Lilly, J. M., Srivastava, D., & Feigh, K. M. (2023). The role of shared mental models in human-AI teams: A theoretical review. *Theoretical Issues in Ergonomics Science*, 24(2), 129–175. <https://doi.org/10.1080/1463922X.2022.2061080>
- Arai, N. H., Masukawa, R., & Miyashita, H. (2023). Designing research-map: A revolutionary scholar support platform achieved through human-AI collaboration. In Meen T.-H. (Ed.), *Proceeding IEEE International Conference on Knowledge Innovation and Invention, ICKII* (pp. 367–371). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICKII58656.2023.10332787>
- Arias-Rosales, A. (2022). The perceived value of human-AI collaboration in early shape exploration: An exploratory assessment. *PLoS One*, 17(9), e0274496. <https://doi.org/10.1371/journal.pone.0274496>
- Arksey, H., & O'Malley, L. (2005). Scoping studies: Towards a methodological framework. *International Journal of Social Research Methodology*, 8(1), 19–32. <https://doi.org/10.1080/1364557032000119616>
- Armaselu, F. (2024). Playing the imitation game: Human-AI simulators in pedagogic design. In F. Lorig, J. Tucker, A. D. Lindstrom, F. Dignum, P. Murukannaiah, A. Theodorou, & P. Yolum (Eds.), *HAI 2024: Hybrid human AI systems for the social good* (pp. 46–54). Vol. 386. IOS Press BV. <https://doi.org/10.3233/FAIA240181>
- Arous, I., Yang, J., Khayati, M., & Cudré-Mauroux, P. (2020). OpenCrowd: A human-AI collaborative approach for finding social influencers via open-ended answers aggregation. In *Proceedings of The Web Conference 2020 (WWW '20)* (pp. 1851–1862). Association for Computing Machinery. <https://doi.org/10.1145/3366423.3380254>
- Arun Kumar, A. V., Rana, S., Shilton, A., & Venkatesh, S. (2022). Human-AI Collaborative Bayesian Optimisation. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (Eds.), *Advances in neural information processing systems* (pp. 1–13, Vol. 35). Neural Information Processing Systems Foundation.
- Ashktorab, Z., Desmond, M., Johnson, J. M., Pan, Q., Dugan, C., Brachman, M., & Spina, C. (2023). SME-in-the-loop: Interaction

- preferences when supervising bots in human-AI communities. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference (DIS '23)* (pp. 2281–2303). Association for Computing Machinery. <https://doi.org/10.1145/3563657.3596100>
- Ashktorab, Z., Dugan, C., Johnson, J., Pan, Q., Zhang, W., Kumaravel, S., & Campbell, M. (2021). Effects of communication directionality and AI agent differences in human-AI interaction. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*, (pp. 1–15). Association for Computing Machinery. <https://doi.org/10.1145/3411764.3445256>
- Ashktorab, Z., Liao, Q. V., Dugan, C., Johnson, J., Pan, Q., Zhang, W., Kumaravel, S., & Campbell, M. (2020). Human-AI collaboration in a cooperative game setting: Measuring social perception and outcomes. *Proceedings of the ACM on Human-Computer Interaction*, 4(CSCW2), 1–20. <https://doi.org/10.1145/3415167>
- Askarisichani, O., Bullo, F., Friedkin, N. E., & Singh, A. K. (2022). Predictive models for human-AI nexus in group decision making. *Annals of the New York Academy of Sciences*, 1514(1), 70–81. <https://doi.org/10.1111/nyas.14783>
- Atkins, A. A., Brown, M. S., & Dancy, C. L. (2021). Examining the effects of race on human-AI cooperation. In R. Thomson, M. N. Hussain, C. Dancy, & A. Pyke (Eds.), *Lecture Notes in Computer Science*, LNCS (Vol. 12720, pp. 279–288). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-80387-2\\_27](https://doi.org/10.1007/978-3-030-80387-2_27)
- Attig, C., Wollstadt, P., Schrills, T., Franke, T., & Wiebel-Herboth, C. B. (2024). More than task performance: Developing new criteria for successful human-AI teaming using the cooperative card game Hanabi. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)* (pp. 1–11). Association for Computing Machinery. <https://doi.org/10.1145/3613905.3650853>
- Babbar, V., Bhatt, U., & Weller, A. (2022). On the utility of prediction sets in human-AI teams. In L. De Raedt & L. De Raedt (Eds.), *IJCAI International Joint Conferences on Artificial Intelligence* (pp. 2457–2463).
- Bach, T. A., Kristiansen, J. K., Babic, A., & Jacovi, A. (2024). Unpacking human-AI interaction in safety-critical industries: A systematic literature review. *IEEE Access*, 12, 106385–106414. <https://doi.org/10.1109/ACCESS.2024.3437190>
- Baniecki, H., Sobieski, B., Bombiński, P., Szatkowski, P., & Biecek, P. (2023). Hospital length of stay prediction based on multi-modal data towards trustworthy human-AI collaboration in radiomics. In J. M. Juarez, M. Marcos, G. Stiglic, & A. Tucker (Eds.), *Lecture Notes in Computer Science*, Vol. 13897, LNAI (pp. 65–74). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-34344-5\\_9](https://doi.org/10.1007/978-3-031-34344-5_9)
- Bannon, L. J., & Schmidt, K. (1989). CSCW – Four characters in search of a context. *DAIMI Report Series*, 18(289), 1–20. <https://doi.org/10.7146/dpb.v18i289.6667>
- Bansal, G., Nushi, B., Kamar, E., Weld, D. S., Lasecki, W. S., & Horvitz, E. (2019a). Beyond accuracy: The role of mental models in human-AI team performance. In E. Law & J. W. Vaughan (Eds.), *Proceedings AAAI Conference on Human Computer Crowdsourcing* (pp. 2–11, Vol. 7). Association for the Advancement of Artificial Intelligence. <https://doi.org/10.1609/hcomp.v7i1.5285>
- Bansal, G., Nushi, B., Kamar, E., Weld, D. S., Lasecki, W. S., & Horvitz, E. (2019b). Updates in human-AI teams: Understanding and addressing the performance/compatibility tradeoff. In *AAAI Conf. Artif. Intell., AAAI Innov. Appl. Artificience Conf., IAAI AAAI Symp. Educ. Adv. Artif. Intell., EAAI* (pp. 2429–2437). AAAI Press.
- Bao, Y., Cheng, X., Vreede, T. d., & de Vreede, G.-J. (2021). Investigating the relationship between AI and trust in human-AI collaboration. In Bui T.X. (Ed.), *Proceedings Annual Hawaii International Conference on System Science*. (Vol. 2020, pp. 607–616). IEEE Computer Society.
- Bao, Y., Gong, W., & Yang, K. (2023). A literature review of human-AI synergy in decision making: From the perspective of affordance actualization theory. *Systems*, 11(9), 442. <https://doi.org/10.3390/systems11090442>
- Bar-Ilan, J. (2018). Tale of three databases: The implication of coverage demonstrated for a sample query. *Frontiers in Research Metrics and Analytics*, 3, 6.
- Baruwal Chhetri, M., Tariq, S., Singh, R., Jalalvand, F., Paris, C., & Nepal, S. (2024). Towards human-AI teaming to mitigate alert fatigue in security operations centres. *ACM Transactions on Internet Technology*, 24(3), 1–22. <https://doi.org/10.1145/3670009>
- Boy, G. A. (2024). Human systems integration of human-AI teaming. In M. Hou, T. H. Falk, A. Mohammadi, A. Guerrieri, and D. Kaber (Eds.), *IEEE Int. Conf. Hum.-Mach. Syst., ICHMS*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICHMS59971.2024.10555843>
- Ben Chaaben, E. (2024). Exploring human-AI collaboration and explainability for sustainable ML. In F. Lorig, J. Tucker, A. D. Lindstrom, F. Dignum, P. Murukannaiah, A. Theodorou, and P. Yolum (Eds.), *HAI 2024: Hybrid Human AI Systems for the Social Good* (pp. 363–370, Vol. 386). IOS Press BV. <https://doi.org/10.3233/FAIA240209>
- Bendell, R., Williams, J., Fiore, S. M., & Jentsch, F. (2021). Supporting social interactions in human-AI teams: Profiling human teammates from sparse data. In *Proc Hum Factors Ergon Soc.* (pp. 665–669, Vol. 65). SAGE Publications Inc. <https://doi.org/10.1177/1071181321651354b>
- Bendoly, E., Chandrasekaran, A., Lima, M. D. R. F., Handfield, R., Khajavi, S. H., & Roscoe, S. (2024). The role of generative design and additive manufacturing capabilities in developing human-AI symbiosis: Evidence from multiple case studies. *Decision Sciences*, 55(4), 325–345. <https://doi.org/10.1111/dec.12619>
- Benefo, E. O., Tingler, A., White, M., Cover, J., Torres, L., Broussard, C., Shirmohammadi, A., Pradhan, A. K., & Patra, D. (2022). Ethical, legal, social, and economic (ELSE) implications of artificial intelligence at a global level: A scientometrics approach. *AI and Ethics*, 2(4), 667–682. <https://doi.org/10.1007/s43681-021-00124-6>
- Berberian, B., Guillou, M. L., & Pagliari, M. (2023). Communicating AI intentions to boost human AI cooperation. In P. K. Murukannaiah and T. Hirzle (Eds.), *CEUR Workshop Proceeding* (pp. 145–149, Vol. 3456). CEUR-WS.
- Bernardo, E. L., & Seva, R. R. (2024). Exploration of explainable AI for trust development on human-AI interaction. In *Proceedings of the 2023 6th Artificial Intelligence and Cloud Computing Conference (AICCC '23)* (pp. 238–246). Association for Computing Machinery. <https://doi.org/10.1145/3639592.3639625>
- Berretta, S., Tausch, A., Ontrup, G., Gilles, B., Peifer, C., & Kluge, A. (2023). Defining human-AI teaming the human-centered way: A scoping review and network analysis. *Frontiers in Artificial Intelligence*, 6, 1250725. <https://doi.org/10.3389/frai.2023.1250725>
- Berretta, S., Tausch, A., Peifer, C., & Kluge, A. (2023). The Job perception inventory: Considering human factors and needs in the design of human-AI work. *Frontiers in Psychology*, 14, 1128945. <https://doi.org/10.3389/fpsyg.2023.1128945>
- Bhardwaj, A., Yang, J., & Cudré-Mauroux, P. (2020). A human-AI loop approach for joint keyword discovery and expectation estimation in micropost event detection. In *AAAI—AAAI Conf. Artif. Intell.* (pp. 2451–2458). AAAI press.
- Bhattacharya, A. (2024). Towards directive explanations: Crafting explainable AI systems for actionable human-AI interactions. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3638177>
- Bian, W., Song, Y., Gu, N., Chan, T. Y., Lo, T. T., Li, T. S., Wong, K. C., Xue, W., & Trillo, R. A. (2023). MoMusic: A motion-driven human-AI collaborative music composition and performing system. In Williams B., Chen Y., and Neville J. (Eds.), *Proceeding AAAI Conf. Artif. Intell., AAAI* (Vol. 37, pp. 16057–16062). AAAI Press.
- Bienefeld, N., Keller, E., & Grote, G. (2024). Human-AI teaming in critical care: A comparative analysis of data scientists' and clinicians' perspectives on AI augmentation and automation. *Journal of Medical Internet Research*, 26, e50130. <https://doi.org/10.2196/50130>
- Bienefeld, N., Kolbe, M., Camen, G., Huser, D., & Buehler, P. K. (2023). Human-AI teaming: Leveraging transactive memory and

- speaking up for enhanced team effectiveness. *Frontiers in Psychology*, 14, 1208019. <https://doi.org/10.3389/fpsyg.2023.1208019>
- Biloborodova, T., & Skarga-Bandurova, I. (2023). Human-AI collaboration in decision making: An initial reliability study and methodology. In *Proceeding IEEE Int. Conf. Intell. Data Acquis. Adv. Comput. Syst.: Technol. Appl., IDAACS* (pp. 1151–1155). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/IDAACS58523.2023.10348928>
- Bingley, W. J., Curtis, C., Lockey, S., Bialkowski, A., Gillespie, N., Haslam, S. A., Ko, R. K. L., Steffens, N., Wiles, J., & Worthy, P. (2023). Where is the human in human-centered AI? Insights from developer priorities and user experiences. *Computers in Human Behavior*, 141, 107617. <https://doi.org/10.1016/j.chb.2022.107617>
- Biyani, P., Bajpai, Y., Radhakrishna, A., Soares, G., & Gulwani, S. (2024). RUBICON: Rubric-based evaluation of domain-specific human AI conversations. In *Proceedings of the 1st ACM International Conference on AI-Powered Software (AIware 2024)* (pp. 161–169). Association for Computing Machinery. <https://doi.org/10.1145/3664646.3664778>
- Block, J. (1995). A contrarian view of the five-factor approach to personality description. *Psychological Bulletin*, 117(2), 187–215. <https://doi.org/10.1037/0033-2909.117.2.187>
- Bogdanova, K. (2024). Aesthetics of algorithmic care: Designing alternative human-AI collaboration practices for digital phenotyping. In *Companion Publication of the 2024 ACM Designing Interactive Systems Conference (DIS '24 Companion)* (pp. 59–61). Association for Computing Machinery. <https://doi.org/10.1145/3656156.3665127>
- Boggust, A., Hoover, B., Satyanarayan, A., & Strobel, H. (2022). Shared interest: Measuring human-AI alignment to identify recurring patterns in model behavior. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3501965>
- Bol, J. A., Sheffel, A., Zia, N., & Meghani, A. (2023). How to address the geographical bias in academic publishing. *BMJ Global Health*, 8(12), e013111. <https://doi.org/10.1136/bmjgh-2023-013111>
- Bondi, E., Koster, R., Sheahan, H., Chadwick, M., Bachrach, Y., Cemgil, T., Paquet, U., & Dvijotham, K. (2022). Role of human-AI interaction in selective prediction. In *Proceeding AAAI Conf. Artif. Intell., AAAI*, (pp. 5286–5294, Vol. 36). Association for the Advancement of Artificial Intelligence.
- Bossen, C., & Pine, K. H. (2023). Batman and Robin in healthcare knowledge work: Human-AI collaboration by clinical documentation integrity specialists. *ACM Transactions on Computer-Human Interaction*, 30(2), 1–29. <https://doi.org/10.1145/3569892>
- Bousdekis, S., Wellsandt, E., Bosani, K., Lepenioti, D., Apostolou, K., Hribernik, & G., Mentzas. (2021). Human-AI Collaboration in Quality Control with Augmented Manufacturing Analytics. In A. Dolgui, A. Bernard, D. Lemoine, von G. Cieminski, and D. Romero (Eds.), *IFIP Advances in Information and Communication Technology* (pp. 303–310, Vol. 633). Springer. [https://doi.org/10.1007/978-3-030-85910-7\\_32](https://doi.org/10.1007/978-3-030-85910-7_32)
- Bozdag, A. A. (2023). AIsmosis and the pas de deux of human-AI interaction: Exploring the communicative dance between society and artificial intelligence. *Online Journal of Communication and Media Technologies*, 13(4), e202340. <https://doi.org/10.30935/ojcm/13414>
- Brachman, M., Ashktorab, Z., Desmond, M., Duesterwald, E., Dugan, C., Nath Joshi, N., Pan, Q., & Sharma, A. (2022). Reliance and automation for human-AI collaborative data labeling conflict resolution. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW2), 1–27. <https://doi.org/10.1145/3555212>
- Brandtzaeg, P. B., Skjuve, M., & Følstad, A. (2022). My AI friend: How users of a social chatbot understand their human-AI friendship. *Human Communication Research*, 48(3), 404–429. <https://doi.org/10.1093/hcr/hqac008>
- Brandtzaeg, P. B., You, Y., Wang, X., & Lao, Y. (2023). Good” and “Bad” Machine Agency in the Context of Human-AI Communication: The Case of ChatGPT. In Degen H., Ntoa S., and Moallem A. (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 14059, pp. 3–23) LNCS. Springer. [https://doi.org/10.1007/978-3-031-48057-7\\_1](https://doi.org/10.1007/978-3-031-48057-7_1)
- Braun, M., Greve, M., & Gnewuch, U. (2023). The new dream team? A review of human-AI collaboration research from a human teamwork perspective. In *International Conference on Information Systems, ICIS: Rising like Phoenix: Emerg. Pandemic Reshaping Hum. Endeavors Digit. Technol.* Association for Information Systems.
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp063oa>
- Bruni, S. (2024). A retrospective engineering analysis of human-AI teams using the sidekick principles. In *Conf Proc IEEE SOUTHEASTCON* (pp. 1368–1369). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/SoutheastCon52093.2024.10500218>
- Brusilovsky, P. (2024). AI in education, learner control, and human-AI collaboration. *International Journal of Artificial Intelligence in Education*, 34(1), 122–135. <https://doi.org/10.1007/s40593-023-00356-z>
- Bui, L., Pezzola, M., & Bandara, D. (2023). How do AI explanations affect human-AI trust?. In *Lecture Notes in Computer Science*, H. Degen & S. Ntoa (Eds.) (Vol. 14050, pp. 175–183). Springer. [https://doi.org/10.1007/978-3-031-35891-3\\_12](https://doi.org/10.1007/978-3-031-35891-3_12)
- Burukina, O. (2020). Human-AI collaboration development: Interim communication rivalry of generation. In Ahram T. (Ed.), *Adv. Intell. Sys. Comput.* (Vol. 965, pp. 70–82). Springer. [https://doi.org/10.1007/978-3-030-20454-9\\_7](https://doi.org/10.1007/978-3-030-20454-9_7)
- Buschek, D., Mecke, L., Lehmann, F., & Dang, H. (2021). Nine potential pitfalls when designing human-AI co-creative Systems. In D. Glowacka & V. Krishnamurthy (Eds.), *CEUR Workshop Proceeding*, Vol. 2903. CEUR-WS.
- Butler, M., Holloway, L. M., Reinders, S., Goncu, C., & Marriott, K. (2021). Technology developments in touch-based accessible graphics: A systematic review of research 2010–2020. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1–15). ACM. <https://doi.org/10.1145/3411764.3445207>
- Buçinca, Z. (2024). Optimizing decision-maker's intrinsic motivation for effective human-AI decision-making. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3638179>
- Cabitza, F., Campagner, A., Ronzio, L., Cameli, M., Mandoli, G. E., Pastore, M. C., Sconfienza, L. M., Folgado, D., Barandas, M., & Gamboa, H. (2023). Rams, hounds and white boxes: Investigating human-AI collaboration protocols in medical diagnosis. *Artificial Intelligence in Medicine*, 138, 102506. <https://doi.org/10.1016/j.artmed.2023.102506>
- Cabitza, F., Campagner, A., & Sconfienza, L. M. (2021). Studying human-AI collaboration protocols: The case of the Kasparov's law in radiological double reading. *Health Information Science and Systems*, 9(1). <https://doi.org/10.1007/s13755-021-00138-8>
- Cabitza, F., Fregosi, C., Campagner, A., & Natali, C. (2024). Explanations considered harmful: The impact of misleading explanations on accuracy in hybrid human-AI decision making. In L. Longo, S. Lapuschkin & C. Seifert (Eds.), *Explainable artificial intelligence* (pp. 255–269). Springer Nature. [https://doi.org/10.1007/978-3-031-63803-9\\_14](https://doi.org/10.1007/978-3-031-63803-9_14)
- Cabrera, Á. A., Perer, A., & Hong, J. I. (2023). Improving human-AI collaboration with descriptions of AI behavior. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW1), 1–21. <https://doi.org/10.1145/3579612>
- Cabrero-Daniel, B., Herda, T., Pichler, V., & Eder, M. (2024). Exploring human-AI collaboration in agile: Customised LLM meeting assistants. In Šmite D., Guerra E., Wang X., Marchesi M., and Gregory P. (Eds.), *Lect. Notes Bus. Inf. Process* (Vol. 512, pp. 163–178). Springer. [https://doi.org/10.1007/978-3-031-61154-4\\_11](https://doi.org/10.1007/978-3-031-61154-4_11)
- Cai, C. J., Winter, S., Steiner, D., Wilcox, L., & Terry, M. (2019). Hello AI: Uncovering the onboarding needs of medical practitioners for human-AI collaborative decision-making. *Proceedings of the ACM on Human-Computer Interaction*, 3(CSCW). <https://doi.org/10.1145/3359206>
- Cai, Z. (2024). Description: An intuitive human-AI collaborative 3D modeling approach. In *Proceedings of the 11th International Conference on*



- Digital and Interactive Arts (ARTECH '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3632776.3632785>
- Caldwell, S., Sweetser, P., O'Donnell, N., Knight, M. J., Aitchison, M., Gedeon, T., Johnson, D., Brereton, M., Gallagher, M., & Conroy, D. (2022). An agile new research framework for hybrid human-AI teaming: Trust, transparency, and transferability. *ACM Transactions on Interactive Intelligent Systems*, 12(3), 1–36. <https://doi.org/10.1145/3514257>
- Calisto, F. M., Santiago, C., Nunes, N., & Nascimento, J. C. (2022). BreastScreening-AI: Evaluating medical intelligent agents for human-AI interactions. *Artificial Intelligence in Medicine*, 127, 102285. <https://doi.org/10.1016/j.artmed.2022.102285>
- Cannanure, V. K., Brown, T. X., & Ogan, A. (2020). DIA: A human AI hybrid conversational assistant for developing contexts. In *Proceedings of the 2020 International Conference on Information and Communication Technologies and Development (ICTD '20)*. Association for Computing Machinery. <https://doi.org/10.1145/3392561.3397577>
- Canonico, L. B., Vakeel, V., Dominic, J., Rodeghero, P., & McNeese, N. (2020). Human-AI partnerships for chaos engineering. In *Proceedings of the IEEE/ACM 42nd International Conference on Software Engineering Workshops (ICSEW'20)* (pp. 499–503). Association for Computing Machinery. <https://doi.org/10.1145/3387940.3391493>
- Cao, S., Gomez, C., & Huang, C.-M. (2023). How time pressure in different phases of decision-making influences human-AI collaboration. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW2), 1–26. <https://doi.org/10.1145/3610068>
- Capel, T., & Brereton, M. (2023). What is Human-centered about human-centered AI? A map of the research landscape. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1–23). <https://doi.org/10.1145/3544548.3580959>
- Carroll, M., Shah, R., Ho, M. K., Griffiths, T. L., Seshia, S. A., Abbeel, P., & Dragan, A. (2019). On the utility of learning about humans for human-AI coordination. In *Advances in neural information processing systems* (pp. 5174–5185, Vol. 32). Neural Information Processing Systems Foundation.
- Casini, L., Marchetti, N., Montanucci, A., Orrù, V., & Rocchetti, M. (2023). A human-AI collaboration workflow for archaeological sites detection. *Scientific Reports*, 13(1). <https://doi.org/10.1038/s41598-023-36015-5>
- Cau, F. M., & Spano, L. D. (2024). Mitigating human errors and cognitive bias for human-AI synergy in cybersecurity. In Breve B., Desolda G., Deufemia V., & Spano L.D. (Eds.), *CEUR Workshop Proceeding* (Vol. 3713, pp. 1–8). CEUR-WS.
- Carolina Centeio, J., Tielman, M. L., & Jonker, C. M. (2022). Artificial trust as a tool in human-AI teams. In *Proceedings of the 2022 ACM/IEEE International Conference on Human-Robot Interaction (HRI '22)* (pp. 1155–1157). IEEE Press.
- Chakravorti, T., Singh, V., Rajtmajer, S., McLaughlin, M., Fraleigh, R., Griffin, C., Kwasnica, A., Pennock, D., & Giles, C. L. (2023). Artificial Prediction markets present a novel opportunity for human-AI collaboration. In *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems (AAMAS '23)* (pp. 2304–2306). International Foundation for Autonomous Agents and Multiagent Systems.
- Chang, R., & Huang, Y. (2021). Towards AI aesthetics: Human-AI collaboration in creating Chinese landscape painting. In Rauterberg M. (Ed.), *Lecture Notes in Computer Science* Vol. 12794 (pp. 213–224). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-77411-0\\_15](https://doi.org/10.1007/978-3-030-77411-0_15)
- Chattopadhyay, P., Yadav, D., Prabhu, V., Chandrasekaran, A., Das, A., Lee, S., Batra, D., & Parikh, D. (2017). Evaluating visual conversational agents via cooperative human-AI games. In Dow S. and Tauman A. (Eds.), *Proceeding AAAI Conference on Human Computer Crowdsourcing, HCOMP* (pp. 2–10). AAAI Press.
- Chen, H., Cohen, E., Wilson, D., & Alfred, M. (2024). A machine learning approach with human-AI collaboration for automated classification of patient safety event reports: Algorithm development and validation study. *JMIR Human Factors*, 11(1), e53378. <https://doi.org/10.2196/53378>
- Chen, V., Liao, Q. V., Wortman Vaughan, J., & Bansal, G. (2023). Understanding the role of human intuition on reliance in human-AI decision-making with explanations. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW2), 1–32. <https://doi.org/10.1145/3610219>
- Chen, X., Wu, C.-S., Murakhov'ska, L., Laban, P., Niu, T., Liu, W., & Xiong, C. (2023). Marvista: Exploring the design of a human-AI collaborative news reading tool. *ACM Transactions on Computer-Human Interaction*, 30(6), 1–27. <https://doi.org/10.1145/3609331>
- Chen, Z., & Schmidt, R. (2024). Exploring a behavioral model of “positive friction” in human-AI interaction. In A. Marcus, E. Rosenzweig, & M. M. Soares (Eds.), *Lecture Notes in Computer Science* (Vol. 14713, pp. 3–22). Springer. [https://doi.org/10.1007/978-3-031-61353-1\\_1](https://doi.org/10.1007/978-3-031-61353-1_1)
- Cheng, R., Smith-Renner, A., Zhang, K., Tetreault, J. R., & Jaimes, A. (2022). Mapping the design space of human-AI interaction in text summarization. In *NAACL – Conference North American Chapter association for computational linguistics: Human language technologies proceeding conference* (pp. 431–455). Association for Computational Linguistics (ACL).
- Chiang, C.-W., Lu, Z., Li, Z., & Yin, M. (2023). Are two heads better than one in AI-assisted decision making? Comparing the behavior and performance of groups and individuals in human-AI collaborative recidivism risk assessment. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3581015>
- Chine, D. R., Brentley, C., Thomas-Browne, C., Richey, J. E., Gul, A., Carvalho, P. F., Branstetter, L., & Koedinger, K. R. (2022). Educational equity through combined human-AI personalization: A propensity matching evaluation. In M. M. Rodrigo, N. Matsuda, A. I. Cristea, & V. Dimitrova (Eds.), *Lecture Notes in Computer Science* (Vol. 13355, pp. 366–377). Springer. [https://doi.org/10.1007/978-3-031-11644-5\\_30](https://doi.org/10.1007/978-3-031-11644-5_30)
- Choi, S., Lee, H., Lee, Y., & Kim, J. (2024). VIVID: Human-AI collaborative authoring of vicarious dialogues from lecture videos. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642867>
- Choudhary, V., Marchetti, A., Shrestha, Y. R., & Puranam, P. (2025). Human-AI ensembles: When can they work? *Journal of Management*, 51(2), 536–569. <https://doi.org/10.1177/01492063231194968>
- Chugh, K., Solis, A. Y., & Latoza, T. D. (2019). Editable AI: Mixed human-AI authoring of code patterns. In J. Smith, C. A. Bogart, J. Good, & S. D. Fleming (Eds.), *Proceedings of IEEE symposium on visual languages and human-centered computing, VL/HCC* (Vol. 2019, pp. 35–43). IEEE Computer Society. <https://doi.org/10.1109/VLHCC.2019.8818871>
- Chung, J. J. Y., Chang, M., & Adar, E. (2022). Gestural inputs as control interaction for generative human-AI co-creation. In A. Smith-Renner & O. Amir (Eds.), *CEUR Workshop Proceeding* (Vol. 3124, pp. 46–55). CEUR-WS.
- Cichocki, A., & Kuleshov, A. P. (2021). Future trends for human-AI collaboration: A comprehensive taxonomy of AI/AGI using multiple intelligences and learning styles. *Computational Intelligence and Neuroscience*, 2021(1), 8893795. <https://doi.org/10.1155/2021/8893795>
- Ciriello, R. F., Hannon, O., Chen, A. Y., & Vaast, E. (2024). Ethical tensions in human-AI companionship: A dialectical inquiry into Replika. In Bui T.X. (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (pp. 488–497). IEEE Computer Society.
- Codella, N. C. F., Lin, C.-C., Halpern, A., Hind, M., Feris, R., & Smith, J. R. (2018). Collaborative human-AI (CHAI): Evidence-based interpretable melanoma classification in dermoscopic images. In Z. Taylor, M. Reyes, M. J. Cardoso, C. A. Silva, D. Stoyanov, L. Maier-Hein, S. Pereira, S. M. Kia, I. Oguz, B. Landman, A. Martel, E. Duchesnay, T. Lofstedt, A. F. Marquand, and R. Meier (Eds.), *Lecture Notes in Computer Science* (Vol. 11038, pp. 97–105). Springer. [https://doi.org/10.1007/978-3-030-02628-8\\_11](https://doi.org/10.1007/978-3-030-02628-8_11)



- Collazo, C., Vargas, I., Cara, B., Weinheimer, C. J., Grabau, R. P., Goldgof, D., Hall, L., Wickline, S. A., & Pan, H. (2024). Synergizing deep learning-enabled preprocessing and human-AI integration for efficient automatic ground truth generation. *Bioengineering*, 11(5), 434. <https://doi.org/10.3390/bioengineering11050434>
- Constantinides, P., Monteiro, E., & Mathiassen, L. (2024). Human-AI joint task performance: Learning from uncertainty in autonomous driving systems. *Information and Organization*, 34(2), 100502. <https://doi.org/10.1016/j.infoandorg.2024.100502>
- Contucci, P., Kertész, J., & Osabutey, G. (2022). Human-AI ecosystem with abrupt changes as a function of the composition. *PLoS One*, 17(5), e0267310. <https://doi.org/10.1371/journal.pone.0267310>
- Correia, (2024). On the human-AI metaphorical interplay for culturally sensitive generative AI design in music co-creation. In A. Soto and E. Zangerle (Eds.), *CEUR Workshop Proceeding* (Vol. 3660). CEUR-WS.
- Correia, B., Fonseca, H., Paredes, R., Chaves, D., Schneider, S., & Jameel. (2021). Determinants and predictors of intentionality and perceived reliability in human-AI interaction as a means for innovative scientific discovery. In Y. Chen, H. Ludwig, Y. Tu, U. Fayyad, X. Zhu, X. T. Hu, S. Byna, X. Liu, J. Zhang, S. Pan, V. Papalexakis, J. Wang, A. Cuzzocrea, & C. Ordonez (Eds.), *Proceeding - IEEE International Conference on Big Data* (pp. 3681–3684). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/BigData52589.2021.9671358>
- Correia, A., Grover, A., Jameel, S., Schneider, D., Antunes, P., & Fonseca, B. (2023). A hybrid human-AI tool for scientometric analysis. *Artificial Intelligence Review*, 56(S1), 983–1010. <https://doi.org/10.1007/s10462-023-10548-7>
- Correia, A., Jameel, S., Schneider, D., Paredes, H., & Fonseca, B. (2020). A workflow-based methodological framework for hybrid human-AI enabled scientometrics. In X. Wu, C. Jermaine, L. Xiong, X. T. Hu, O. Kotevska, S. Lu, W. Xu, S. Aluru, C. Zhai, E. Al-Masri, Z. Chen, & J. Saltz (Eds.), *Proceeding - IEEE International Conference on Big Data* (pp. 2876–2883). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/BigData50022.2020.9378096>
- Correia, A., & Lindley, S. (2022). Collaboration in relation to human-AI systems: Status, trends, and impact. In S. Tsumoto, Y. Ohsawa, L. Chen, D. Van den Poel, X. Hu, Y. Motomura, T. Takagi, L. Wu, Y. Xie, A. Abe, & Raghavan V. (Eds.), *Proceeding - IEEE International Conference on Big Data* (pp. 3417–3422). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/BigData55660.2022.10020416>
- Correia, A., Schneider, D., Fonseca, B., Mohseni, H., Kujala, T., & Kärkkäinen, T. (2024). And justice for art(ists): Metaphorical design as a method for creating culturally diverse human-AI music composition experiences. In *Proceeding HORA - International Conference Human - Human-Computer Interaction, Optimization and Robotic Applications*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/HORA61326.2024.10550680>
- Cotino Arbelo, A. E., Gonzalez-Gonzalez, C. S., & Molina Gil, J. M. (2023). Embracing the future: Unveiling the revolution of human-AI interaction in the digital education era. In F. Moreira, C. S. Gonzalez-Gonzalez, A. Infante-Moro, J. C. Infante-Moro, J. Gallardo-Perez, A. Garcia-Holgado, & F. J. Garcia-Penalvo (Eds.), *Proceeding - JICV: International Conferences on Virtual Campus*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/JICV59748.2023.10565703>
- Crompton, L. (2021). The decision-point-dilemma: Yet another problem of responsibility in human-AI interaction. *Journal of Responsible Technology*, 7–8, 100013. <https://doi.org/10.1016/j.jrt.2021.100013>
- Cummings, P., Schurr, N., Naber, A., & Serfaty, D. (2021). Recognizing artificial intelligence: The key to unlocking human AI teams. In *Systems engineering and artificial intelligence* (pp. 23–45). Springer International Publishing. [https://doi.org/10.1007/978-3-030-77283-3\\_2](https://doi.org/10.1007/978-3-030-77283-3_2)
- Dai, S., Li, Y., Grace, K., & Globa, A. (2023). Towards human-AI collaborative architectural concept design via semantic AI. In M. Turrin, C. Andriotis, & A. Rafiee (Eds.), *Communications in computer and information science CCIS* (Vol. 1819, pp. 68–82). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-37189-9\\_5](https://doi.org/10.1007/978-3-031-37189-9_5)
- Daish, P., Micallef, N., Lorenzo-Dus, N., Paiement, A., & Sahoo, D. (2024). Towards co-designing a continuous-learning human-AI interface: A case study in online grooming detection. In A. Dix, M. Roach, T. Turchi, A. Malizia, & B. Wilson (Eds.), *CEUR Workshop Proceeding* (Vol. 3701). CEUR-WS.
- Daniel-Saad, A., Kuflik, T., Weiss, P., & Schreuer, N. (2013). Building an ontology for assistive technology using the Delphi method. *Disability and Rehabilitation*, 8(4), 275–286. <https://doi.org/10.3109/17483107.2012.723238>
- Dawood, K. A., Sharif, K. Y., Ghani, A. A., Zulzalil, H., Zaidan, A. A., & Zaidan, B. B. (2021). Towards a unified criteria model for usability evaluation in the context of open source software based on a fuzzy Delphi method. *Information and Software Technology*, 130, 106453. <https://doi.org/10.1016/j.infsof.2020.106453>
- de Andrade, A. S. L., Jackson, V., Prikladnicki, R., & van der Hoek, A. (2024). On meetings involving remote software teams: A systematic literature review. *Information and Software Technology*, 175, 107541. <https://doi.org/10.1016/j.infsof.2024.107541>
- De Brito Duarte, R. (2023). Towards responsible AI: Developing explanations to increase human-AI collaboration. In P. Lukowicz, S. Mayer, J. Koch, J. Shawe-Taylor, & I. Tiddi (Eds.), *Frontiers in artificial intelligence and applications* (Vol. 368, pp. 470–482). IOS Press BV. <https://doi.org/10.3233/FAIA230126>
- de Visser, E. J., Momen, A., Walliser, J. C., Kohn, S. C., Shaw, T. H., & Tossell, C. C. (2023). Mutually adaptive trust calibration in human-AI teams. In P. K. Murukannaiah & T. Hirzle (Eds.), *CEUR Workshop Proceeding* (Vol. 3456, pp. 188–193). CEUR-WS.
- Del Giudice, M., Scuto, V., Orlando, B., & Mustilli, M. (2023). Toward the human-centered approach. A revised model of individual acceptance of AI. *Human Resource Management Review*, 33(1), 100856. <https://doi.org/10.1016/j.hrmr.2021.100856>
- Dellermann, D., Calma, A., Lipusch, N., Weber, T., Weigel, S., & Ebel, P. (2019). The future of human-AI collaboration: A taxonomy of design knowledge for hybrid intelligence systems. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (Vol. 2019, pp. 274–283). IEEE Computer Society.
- Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering*, 61(5), 637–643. <https://doi.org/10.1007/s12599-019-00595-2>
- Demidova, E. (2018). Can children teach AI? Towards expressive human-AI dialogs. In M. van Erp, K. Srinivas, C. Fortuna, M. Atre, & V. Lopez (Eds.), *CEUR Workshop Proceeding* (Vol. 2180). CEUR-WS.
- Demir, M., McNeese, N. J., & Cooke, N. J. (2019). The evolution of human-autonomy teams in remotely piloted aircraft systems operations. *Frontiers in Communication*, 4, 50. <https://doi.org/10.3389/fcomm.2019.00050>
- Denman, D., Kim, J.-H., Munro, N., Speyer, R., & Cordier, R. (2021). Consensus on terminology for describing child language interventions: A Delphi study. *Journal of Speech, Language, and Hearing Research*, 64(9), 3504–3519. [https://doi.org/10.1044/2021\\_JSLHR-20-00656](https://doi.org/10.1044/2021_JSLHR-20-00656)
- Desolda, G., Dimauro, G., Esposito, A., Lanzilotti, R., Matera, M., & Zancanaro, M. (2024). A human-AI interaction paradigm and its application to rhinocytology. *Artificial Intelligence in Medicine*, 155, 102933. <https://doi.org/10.1016/j.artmed.2024.102933>
- Devitt, S. K. (2024). Bad, mad, and cooked moral responsibility for civilian harms in human-AI military teams. In *Responsible Use of AI in Mil-Systems* (pp. 248–277). CRC Press. <https://doi.org/10.1201/9781003410379-16>
- Dhillon, P. S., Molaei, S., Li, J., Golub, M., Zheng, S., & Robert, L. P. (2024). Shaping human-AI collaboration: Varied scaffolding levels in co-writing with language models. In *Proceedings of the CHI conference on human factors in computing systems* (CHI '24). Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642134>
- Dillenbourg, P. (1999). What do you mean by collaborative learning? In P. Dillenbourg (Ed.), *Collaborative-learning: Cognitive and computational approaches* (p. 1). Elsevier. <https://telearn.hal.science/hal-00190240>
- Ding, Z. (2024). Advancing GUI for generative AI: Charting the design space of human-AI interactions through task creativity and complexity. In *Companion Proceedings of the 29th International*

- Conference on Intelligent User Interfaces (IUI '24 Companion) (pp. 140–143). Association for Computing Machinery. <https://doi.org/10.1145/3640544.3645241>
- Ding, Z., Smith-Renner, A., Zhang, W., Tetreault, J. R., & Jaimes, A. (2023). Harnessing the power of LLMs: Evaluating human-AI text co-creation through the lens of news headline generation. In *Findings of the association for computational linguistics: EMNLP* (pp. 3321–3339). Association for Computational Linguistics (ACL).
- Dodeja, L., Tambwekar, P., Hedlund-Botti, E., & Gombolay, M. (2024). Towards the design of user-centric strategy recommendation systems for collaborative human-AI tasks. *International Journal of Human Computer Studies*, 184, 103216. <https://doi.org/10.1016/j.ijhcs.2023.103216>
- Doherty, K. & Doherty, G. (2018). Engagement in HCI: Conception, theory and measurement. *Computing Surveys*, 51(5), 1–39. <https://doi.org/10.1145/3234149>
- Dolgikh, S. & Mulesa, O. (2021). Collaborative human-AI decision-making systems. In P. Bidyuk, Y. Bodyanskiy, S. Bozoki, L. Huliannytskyi, R. Hubert, S. Lipovetsky, M. Malyar, K. Markov, N. Pankratova, I. Sergienko, V. Snytyuk, M. Sodenkamp, Y. Stoyan, V. Tsyganok, O. Voloshyn, V. Vovk, S. Yakovlev, Y. Zaychenko, & M. Zgurovsky (Eds.), *CEUR Workshop Mil-Systems* (Vol. 3106, pp. 96–105). CEUR-WS.
- Dorton, S. L. & Hall, R. A. (2021). Collaborative human-AI sensemaking for intelligence analysis. In H. Degen & S. Ntoa (Eds.), *Lecture Notes in Computer Science LNAI* (Vol. 12797, pp. 185–201). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-77772-2\\_12](https://doi.org/10.1007/978-3-030-77772-2_12)
- Du, X., An, P., Leung, J., Li, A., Chapman, L. E., & Zhao, J. (2024). DeepThInk: Designing and probing human-AI co-creation in digital art therapy. *International Journal of Human-Computer Studies*, 181, 103139. <https://doi.org/10.1016/j.ijhcs.2023.103139>
- Dubey, A., Abhinav, K., Jain, S., Arora, V., & Puttaveerana, A. (2020). HACO: A framework for developing human-AI teaming. In *Proceedings of the 13th Innovations in Software Engineering Conference (Formerly Known as India Software Engineering Conference) (ISEC '20)* (pp. 1–9). Association for Computing Machinery. <https://doi.org/10.1145/3385032.3385044>
- Duncan, M. C., Miller, M. E., & Borghetti, B. J. (2023). Analysis and requirement generation for defense intelligence search: Addressing data overload through human-AI agent system design for ambient awareness. *Systems*, 11(12), 561. <https://doi.org/10.3390/systems11120561>
- Dynel, M. (2023). Lessons in linguistics with ChatGPT: Metapragmatics, metacommunication, metadiscourse and metalanguage in human-AI interactions. *Language & Communication*, 93, 107–124. <https://doi.org/10.1016/j.langcom.2023.09.002>
- Ebermann, C., Selisky, M., & Weibelzahl, S. (2023). Explainable AI: The effect of contradictory decisions and explanations on users' acceptance of AI systems. *International Journal of Human-Computer Interaction*, 39(9), 1807–1826. <https://doi.org/10.1080/10447318.2022.2126812>
- Echeverria, V., Holstein, K., Huang, J., Sewall, J., Rummel, N., & Alevén, V. (2020). Exploring human-AI control over dynamic transitions between individual and collaborative learning. In C. Alario-Hoyos, M. J. Rodríguez-Triana, M. Scheffel, I. Arnedillo-Sánchez, & S. M. Dennerlein (Eds.), *Lecture Notes in Computer Science LNCS* (Vol. 12315, pp. 230–243). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-57717-9\\_17](https://doi.org/10.1007/978-3-030-57717-9_17)
- Echeverria, V., Yang, K., Lawrence, L., Rummel, N., & Alevén, V. (2023). Designing hybrid human-AI orchestration tools for individual and collaborative activities: A technology probe study. *IEEE Transactions on Learning Technologies*, 16(2), 191–205. <https://doi.org/10.1109/TLT.2023.3248155>
- El-Assady, M. & Moruzzi, C. (2022). Which biases and reasoning pitfalls do explanations trigger decomposing communication processes in human-AI interaction. *IEEE Computer Graphics and Applications*, 42(6), 11–23. <https://doi.org/10.1109/MCG.2022.3200328>
- El-Zanfaly, D., Huang, Y., & Dong, Y. (2022). Sand playground: Designing human-AI physical interface for co-creation in motion. In *Proceedings of the 14th Conference on Creativity and Cognition (C&C '22)* (pp. 49–55). Association for Computing Machinery. <https://doi.org/10.1145/3527927.3532791>
- Endsley, M. R. (2023). Supporting human-AI teams: Transparency, explainability, and situation awareness. *Computers in Human Behavior*, 140, 107574. <https://doi.org/10.1016/j.chb.2022.107574>
- Erdogan, E., Dignum, F., & Verbrugge, R. (2024). Effective maintenance of computational theory of mind for human-AI collaboration. In *HAI 2024: Hybrid Human AI Systems for the Social Good* (Vol. 386, pp. 114–123). IOS Press BV. <https://doi.org/10.3233/FAIA240188>
- Eriksson, C., Olsen, K., Schmager, S., Pappas, I. O., & Vassilakopoulou, P. (2023). Human-AI collaboration in public services: The case of sick leave case handling. In M. Janssen, R. Matheus, L. Pinheiro, F. Frankenberger, Y. K. Dwivedi, I. O. Pappas, & M. Mäntymäki (Eds.), *Lecture Notes in Computer Science LNCS* (Vol. 14316, pp. 41–53). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-50040-4\\_4](https://doi.org/10.1007/978-3-031-50040-4_4)
- Erlei, A., Sharma, A., & Gadiraju, U. (2024). Understanding choice independence and error types in human-AI collaboration. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3641946>
- Fabri, L., Häckel, B., Oberländer, A. M., Rieg, M., & Stohr, A. (2023). Disentangling human-AI hybrids: Conceptualizing the interworking of humans and AI-enabled systems. *Business & Information Systems Engineering*, 65(6), 623–641. <https://doi.org/10.1007/s12599-023-00810-1>
- Fahse, T., & Schmitt, A. (2023). Exploring the synergies in human-AI hybrids: A longitudinal analysis in sales forecasting. In *The annual Americas Conference on Information Systems, AMCIS*. Association for Information Systems.
- Fan, M., Yang, X., Yu, T., Liao, Q. V., & Zhao, J. (2022). Human-AI collaboration for UX evaluation: Effects of explanation and synchronization. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW1), 1–32. <https://doi.org/10.1145/3512943>
- Fan, X., Wu, Z., Yu, C., Rao, F., Shi, W., & Tu, T. (2024). ContextCam: Bridging context awareness with creative human-AI image co-creation. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642129>
- Feng, Y. & Wang, X. (2023). A comparative study on the development of Chinese and English abilities of Chinese primary school students through two bilingual reading modes: Human-AI robot interaction and paper books. *Frontiers in Psychology*, 14, 1200675. <https://doi.org/10.3389/fpsyg.2023.1200675>
- Fernández-Llorca, D., Gómez, E., Sánchez, I., & Mazzini, G. (2024). An interdisciplinary account of the terminological choices by EU policy-makers ahead of the final agreement on the AI Act: AI system, general purpose AI system, foundation model, and generative AI. *Artificial Intelligence and Law*, 1–14. <https://doi.org/10.1007/s10506-024-09412-y>
- Feuston, J. L. & Brubaker, J. R. (2021). Putting tools in their place: The role of time and perspective in human-AI collaboration for qualitative analysis. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2), 1–25. <https://doi.org/10.1145/3479856>
- Fidge, N., Morrison, J., Nugent, T., & Tozuka, M. (1989). Monoclonal antibodies to human AI apolipoprotein and characterisation of cyanogen bromide fragments of apoA-I. *Biochimica et Biophysica Acta*, 1003(1), 84–90. [https://doi.org/10.1016/0005-2760\(89\)90103-3](https://doi.org/10.1016/0005-2760(89)90103-3)
- Figoli, F. A., Mattioli, F., & Rampino, L. (2022). AI in the design process: Training the human-AI collaboration. In E. Bohemia, L. Buck, & H. Grierson (Eds.), *The international conference on engineering and product design education: Disruptive innovation, Regenerate Transform, E PDE*. The Design Society.
- Flathmann, C., Duan, W., Mcneese, N. J., Hauptman, A., & Zhang, R. (2024). Empirically understanding the potential impacts and process of social influence in human-AI teams. *Proceedings of the ACM on Human-Computer Interaction*, 8(CSCW1), 1–32. <https://doi.org/10.1145/3637326>
- Flathmann, C., Schelble, B. G., Rosopa, P. J., McNeese, N. J., Mallick, R., & Madathil, K. C. (2023). Examining the impact of varying levels of AI teammate influence on human-AI teams. *International Journal*



- of *Human-Computer Studies*, 177, 103061. <https://doi.org/10.1016/j.ijhcs.2023.103061>
- Flathmann, C., Schelble, B. G., Zhang, R., & McNeese, N. J. (2021). Modeling and guiding the creation of ethical human-AI teams. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society (AIIES '21)* (pp. 469–479). Association for Computing Machinery. <https://doi.org/10.1145/3461702.3462573>
- Fogliato, R., Chappidi, S., Lungren, M., Fisher, P., Wilson, D., Fitzke, M., Parkinson, M., Eric, H., Kori, I., & Besmira, N. (2022). Who goes first? Influences of human-AI workflow on decision making in clinical imaging. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency (FAccT '22)* (pp. 1362–1374). Association for Computing Machinery. <https://doi.org/10.1145/3531146.3533193>
- Franklin, M. & Lagnado, D. (2022). Human-AI interaction paradigm for evaluating explainable artificial intelligence. In C. Stephanidis, M. Antona, & S. Ntoa (Eds.), *Commun. Comput. Info. Sci. CCIS* (Vol. 1580, pp. 404–411). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-06417-3\\_54](https://doi.org/10.1007/978-3-031-06417-3_54)
- Frattolillo, F., Brandizzi, N., Cipollone, R., & Iocchi, L. (2024). Towards computational models for reinforcement learning in human-AI teams. In N. Brandizzi, C. C. Jorge, R. Cipollone, F. Frattolillo, L. Iocchi, & A.-S. Ulfert-Blank (Eds.), *CEUR Workshop Proceeding* (Vol. 3634, pp. 27–33). CEUR-WS.
- Fu, Z. & Zhou, Y. (2020). Research on human-AI co-creation based on reflective design practice. *CCF Transactions on Pervasive Computing and Interaction*, 2(1), 33–41. <https://doi.org/10.1007/s42486-020-00028-0>
- Fuchs, A., Passarella, A., & Conti, M. (2023). Compensating for sensing failures via delegation in human-AI hybrid systems. *Sensors*, 23(7), 3409. <https://doi.org/10.3390/s23073409>
- Fuchs, A., Passarella, A., & Conti, M. (2024). Optimizing risk-averse human-AI hybrid teams. In *2024 IEEE International Conference on Smart Computing (SMARTCOMP)* (pp. 117–124). <https://doi.org/10.1109/SMARTCOMP61445.2024.00037>
- Gamboa, E., Libreros, A., Hirth, M., & Dubiner, D. (2022). Human-AI collaboration for improving the identification of cars for autonomous driving. In G. Drakopoulos & E. Kafeza (Eds.), *CEUR Workshop Proceeding* (Vol. 3318). CEUR-WS.
- Gammelgård-Larsen, A., van Berkel, N., Skov, M. B., & Kjeldskov, J. (2024). Designing for human-AI interaction: Comparing intermittent, continuous, and proactive interactions for a music application. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3650886>
- Gao, R., Saar-Tsechansky, M., De-Arteaga, M., Han, L., Lee, M. K., & Lease, M. (2021). Human-AI collaboration with bandit feedback. In Z.-H. Zhou (Ed.), *IJCAI Int. Joint Conf. Artif. Intell.* (pp. 1722–1728). International Joint Conferences on Artificial Intelligence.
- Gao, Z. & Jiang, J. (2021). Evaluating human-AI hybrid conversational systems with chatbot message suggestions. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management (CIKM '21)* (pp. 534–544). Association for Computing Machinery. <https://doi.org/10.1145/3459637.3482340>
- García-Valls, M., Dubey, A., & Botti, V. (2018). Introducing the new paradigm of social dispersed computing: Applications, technologies and challenges. *Journal of Systems Architecture*, 91, 83–102. <https://doi.org/10.1016/j.sysarc.2018.05.007>
- Garibay, O. O., Winslow, B., Andolina, S., Antona, M., Bodenschatz, A., Coursaris, C., Falco, G., Fiore, S. M., Garibay, I., Grieman, K., Havens, J. C., Jirotkra, M., Kacorri, H., Karwowski, W., Kider, J., Konstan, J., Koon, S., Lopez-Gonzalez, M., Maifeld-Carucci, I., ... Xu, W. (2023). Six human-centered artificial intelligence grand challenges. *International Journal of Human-Computer Interaction*, 39(3), 391–437. <https://doi.org/10.1080/10447318.2022.2153320>
- Gass, D. F. (2023). Exploring personality-based heterogeneity in meta-knowledge and human-AI collaboration. In *International Conference on Information Systems, ICIS: "Rising like Phoenix: Emerg. Pandemic Reshaping Hum. Endeavors Digit. Technol."* Association for Information Systems.
- Gaurav, N. V., Rekha, M., Kumar, N. J., & Lokesh, A. V. (2024). Human AI collaboration for backend text generation: Dynamic content recommendation (DCR) for websites based on keywords. In *ICCCDS – International Conference on Computing and Data Science* Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICCCDS60734.2024.10560437>
- Gebreegziabher, S. A., Zhang, Z., Tang, X., Meng, Y., Glassman, E. L., & Li, T. J.-J. (2023). PaTAT: Human-AI collaborative qualitative coding with explainable interactive rule synthesis. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3581352>
- Gebreegziabher, S. A., Zhang, Z., Tang, X., Meng, Y., Glassman, E. L., & Li, T. J.-J. (2023). PaTAT: Human-AI collaborative qualitative coding with explainable interactive rule synthesis. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. ACM. <https://doi.org/10.1145/3544548.3581352>
- Georganta, E. & Ulfert, A. (2024). Would you trust an AI team member? Team trust in human-AI teams. *Journal of Occupational and Organizational Psychology*, 97(3), 1212–1241. <https://doi.org/10.1111/joop.12504>
- Gerlich, M. (2024). Exploring motivators for trust in the dichotomy of human-AI trust dynamics. *Social Sciences*, 13(5), 251. <https://doi.org/10.3390/socsci13050251>
- Germanakos, P. (2024). "It's time!" Toward a human-AI quantum experience design paradigm: Reinventing the theoretical framework of HCI. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3650946>
- Gianet, E. T., Di Caro, L., & Rapp, A. (2024). Music composition as a lens for understanding human-AI collaboration. In A. Dix, M. Roach, T. Turchi, A. Malizia, & B. Wilson (Eds.), *CEUR Workshop Proceeding* (Vol. 3701). CEUR-WS.
- Giudici, M., Liguori, F., Tocchetti, A., & Brambilla, M. (2024). Unveiling human-AI interaction and subjective perceptions about artificial intelligent agents. In K. Stefanidis, K. Systä, M. Matera, S. Heil, H. Kondylakis, & E. Quintarelli (Eds.), *Lecture Notes in Computer Science LNCS* (Vol. 14629, pp. 414–418). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-62362-2\\_36](https://doi.org/10.1007/978-3-031-62362-2_36)
- Glinka, K. & Müller-Birn, C. (2023). Critical-reflective human-AI collaboration: Exploring computational tools for art historical image retrieval. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW2), 1–33. <https://doi.org/10.1145/3610054>
- Gmeiner, F., Conlin, J. L., Tang, E. H., Martelaro, N., & Holstein, K. (2024). An evidence-based workflow for studying and designing learning supports for human-AI co-creation. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3650763>
- Gnatzy, T., Warth, J., von der Gracht, H., & Darkow, I.-L. (2011). Validating an innovative real-time Delphi approach – A methodological comparison between real-time and conventional Delphi studies. *Technological Forecasting and Social Change*, 78(9), 1681–1694. <https://doi.org/10.1016/j.techfore.2011.04.006>
- Goel, T., Shaer, O., Delcourt, C., Gu, Q., & Cooper, A. (2023). Preparing future designers for human-AI collaboration in persona creation. In *Proceedings of the 2nd Annual Meeting of the Symposium on Human-Computer Interaction for Work (CHIWORK '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3596671.3598574>
- Gomez, C. E., Sztainberg, M. O., & Trana, R. E. (2022). Curating cyber-bullying datasets: A human-AI collaborative approach. *International Journal of Bullying Prevention*, 4(1), 35–46. <https://doi.org/10.1007/s42380-021-00114-6>
- Gopinath, D., Decastro, J., Rosman, G., Sumner, E., Morgan, A., Hakimi, S., & Stent, S. (2022). HMIway-env: A framework for simulating behaviors and preferences to support human-AI teaming in driving. In *IEEE Computer Society. Conference on Computer Vision and Pattern Recognition Workshops* (Vol. 2022, pp. 4341–4349).

- IEEE Computer Society. <https://doi.org/10.1109/CVPRW56347.2022.00480>
- Goyal, N., Baumler, C., Nguyen, T., & Daumé, H. III. (2024). The impact of explanations on fairness in human-AI decision-making: Protected vs proxy features. In *Proceedings of the 29th International Conference on Intelligent User Interfaces (IUI '24)* (pp. 155–180). Association for Computing Machinery. <https://doi.org/10.1145/3640543.3645210>
- Grabe, I., González-Duque, M., Risi, S., & Zhu, J. (2022). Towards a framework for human-AI interaction patterns in co-creative GAN applications. In A. Smith-Renner & O. Amir (Eds.), *CEUR Workshop Proceeding* (Vol. 3124, pp. 92–102). CEUR-WS.
- Graziani, M., Dutkiewicz, L., Calvaresi, D., Amorim, J. P., Yordanova, K., Vered, M., Nair, R., Abreu, P. H., Blanke, T., Pulignano, V., Prior, J. O., Lauwaert, L., Reijers, W., Depeursinge, A., Andrearczyk, V., & Müller, H. (2023). A global taxonomy of interpretable AI: Unifying the terminology for the technical and social sciences. *Artificial Intelligence Review*, 56(4), 3473–3504. <https://doi.org/10.1007/s10462-022-10256-8>
- Graça, P. & Camarinha-Matos, L. M. (2024). A human-AI centric performance evaluation system for collaborative business ecosystems. In L. M. Camarinha-Matos and F. Ferrada (Eds.), *IFIP Advances in Information and Communication Technology IFIPAICT* (Vol. 716, pp. 3–27). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-63851-0\\_1](https://doi.org/10.1007/978-3-031-63851-0_1)
- Grisold, T. & Schneider, J. (2023). Dynamics of human-AI delegation in organizational routines. In *International Conference on Information Systems, ICIS: "Rising like Phoenix: Emerg. Pandemic Reshaping Hum. Endeavors Digit. Technol."* Association for Information Systems.
- Grosinger, J. (2022). On proactive human-AI systems. In H. Banaee, A. Loutfi, A. Saffioti, A. Lieto, & A. Lieto (Eds.), *CEUR Workshop Proceeding* (Vol. 3400, pp. 140–146). CEUR-WS.
- Gu, H., Liang, Y., Xu, Y., Williams, C. K., Magaki, S., Khanlou, N., Vinters, H., Chen, Z., Ni, S., Yang, C., Yan, W., Zhang, X. R., Li, Y., Haeri, M., & Chen, X. (2023). Improving workflow integration with XPath: Design and evaluation of a human-AI diagnosis system in pathology. *ACM Transactions on Computer-Human Interaction*, 30(2), 1–37. <https://doi.org/10.1145/3577011>
- Gu, H., Yang, C., Haeri, M., Wang, J., Tang, S., Yan, W., He, S., Williams, C. K., Magaki, S., & Chen, X. (2023). Augmenting pathologists with NaviPath: Design and evaluation of a human-AI collaborative navigation system. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3580694>
- Gu, Q., Wang, Y., Hu, X., & Shaer, O. (2024). Exploring the impact of human-AI collaboration on college students' tangible creation: Building poetic scenes with LEGO bricks. In A. Soto & E. Zangerle (Eds.), *CEUR Workshop Proceeding* (Vol. 3660). CEUR-WS.
- Guerdan, L., Raymond, A., & Gunes, H. (2021). Toward affective XAI: Facial affect analysis for understanding explainable human-AI interactions. In *Proceeding IEEE International Conference Computer Vision* (Vol. 2021, pp. 3789–3798). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICCVW54120.2021.00423>
- Guimaraes, D., Paulino, D., Correia, A., Trigo, L., Brazdil, P., & Paredes, H. (2021). Towards a human-AI hybrid framework for inter-researcher similarity detection. In A. Nurnberger, G. Fortino, A. Guerrieri, D. Kaber, D. Mendonca, M. Schilling, & Z. Yu (Eds.), *Proceeding IEEE International Conference on Human Machine Systems, ICHMS*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICHMS53169.2021.9582633>
- Guingrich, R. E. & Graziano, M. S. A. (2024). Ascribing consciousness to artificial intelligence: Human-AI interaction and its carry-over effects on human-human interaction. *Frontiers in Psychology*, 15, 1322781. <https://doi.org/10.3389/fpsyg.2024.1322781>
- Gupta, P., Nguyen, T. N., Gonzalez, C., & Woolley, A. W. (2023). Fostering collective intelligence in human-AI collaboration: Laying the groundwork for COHUMAIN. *Topics in Cognitive Science*, 1–28. <https://doi.org/10.1111/tops.12679>
- Gurney, N., Pynadath, D. V., & Wang, N. (2023). Comparing psychometric and behavioral predictors of compliance during human-AI interactions. In A. Meschtscherjakov, C. Midden, & J. Ham (Eds.), *Lecture Notes in Computer Science LNCS* (Vol. 13832, pp. 175–197). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-30933-5\\_12](https://doi.org/10.1007/978-3-031-30933-5_12)
- Gusenbauer, M. & Haddaway, N. R. (2020). Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources. *Research Synthesis Methods*, 11(2), 181–217. <https://doi.org/10.1002/jrsm.1378>
- Gusenbauer, M. (2022). Search where you will find most: Comparing the disciplinary coverage of 56 bibliographic databases. *Scientometrics*, 127(5), 2683–2745. <https://doi.org/10.1007/s11192-022-04289-7>
- Guttman, R. D., Hammer, J., Harpstead, E., & Smith, C. J. (2021). Play for real(ism) – Using games to predict human-AI interactions in the real world. *Proceedings of the ACM on Human-Computer Interaction*, 5(CHI PLAY), 1–17. <https://doi.org/10.1145/3474655>
- Göbel, K., Niessen, C., Seufert, S., & Schmid, U. (2022). Explanatory machine learning for justified trust in human-AI collaboration: Experiments on file deletion recommendations. *Frontiers in Artificial Intelligence*, 5, 919534. <https://doi.org/10.3389/frai.2022.919534>
- Hagemann, V., Rieth, M., Suresh, A., & Kirchner, F. (2023). Human-AI teams – Challenges for a team-centered AI at work. *Frontiers in Artificial Intelligence*, 6, 1252897. <https://doi.org/10.3389/frai.2023.1252897>
- Haindl, P., Buchgeher, G., Khan, M., & Moser, B. (2022). Towards a reference software architecture for human-AI teaming in smart manufacturing. In *Proceedings of the ACM/IEEE 44th International Conference on Software Engineering: New Ideas and Emerging Results (ICSE-NIER '22)* (pp. 96–100). Association for Computing Machinery. <https://doi.org/10.1145/3510455.3512788>
- Haindl, P., Hoch, T., Dominguez, J., Aperribai, J., Ure, N. K., & Tunçel, M. (2022). Quality characteristics of a software platform for human-AI teaming in smart manufacturing. In A. Vallecillo, J. Visser, & R. Pérez-Castillo (Eds.), *Communications in computer and information science CCIS* (Vol. 1621, pp. 3–17). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-14179-9\\_1](https://doi.org/10.1007/978-3-031-14179-9_1)
- Harris-Watson, A. M., Larson, L. E., Lauharatanahirun, N., DeChurch, L. A., & Contractor, N. S. (2023). Social perception in human-AI teams: Warmth and competence predict receptivity to AI teammates. *Computers in Human Behavior*, 145, 107765. <https://doi.org/10.1016/j.chb.2023.107765>
- Hartikainen, M., Spurava, G., & Väänänen, K. (2024). Human-AI collaboration in smart manufacturing: Key concepts and framework for design. In F. Lorig, J. Tucker, A. D. Lindstrom, F. Dignum, P. Murukannaiah, A. Theodorou, & P. Yolum (Eds.), *Frontiers in artificial intelligence and applications*. (Vol. 386, pp. 162–172). IOS Press BV. <https://doi.org/10.3233/FAIA240192>
- Hassany, M., Ke, J., Brusilovsky, P., Balajee Lekshmi Narayanan, A., & Akhuseyinoglu, K. (2024). Authoring worked examples for JAVA programming with human AI collaboration. In *Proceedings of the 39th ACM/SIGAPP Symposium on Applied Computing (SAC '24)* (pp. 101–103). Association for Computing Machinery. <https://doi.org/10.1145/3605098.3636160>
- Hassany, M., Ke, J., Brusilovsky, P., Arun, B., Lekshmi, N., & Kamil, A. (2024). Human-AI co-creation of worked examples for programming classes. In A. Soto & E. Zangerle (Eds.), *CEUR Workshop Proceeding* (Vol. 3660). CEUR-WS.
- Haupt, M., Freidank, J., & Haas, A. (2025). Consumer responses to human-AI collaboration at organizational frontlines: Strategies to escape algorithm aversion in content creation. *Review of Managerial Science*, 19(2), 377–413. <https://doi.org/10.1007/s11846-024-00748-y>
- Hauptman, A. I., Schelble, B. G., Duan, W., Flathmann, C., & McNeese, N. J. (2024). Understanding the influence of AI autonomy on AI explainability levels in human-AI teams using a mixed methods approach. *Cognition, Technology & Work*, 26(3), 435–455. <https://doi.org/10.1007/s10111-024-00765-7>
- Hauptman, A. I., Schelble, B. G., McNeese, N. J., & Madathil, K. C. (2023). Adapt and overcome: Perceptions of adaptive autonomous



- agents for human-AI teaming. *Computers in Human Behavior*, 138, 107451. <https://doi.org/10.1016/j.chb.2022.107451>
- He, T. & Jazizadeh, F. (2024). Trust in human-AI interaction: Review of empirical research on trust in AI-powered smart home ecosystems. In Y. Turkan, J. Louis, F. Leite, & S. Ergun (Eds.), *Computer Science and Engineering: Data Sensitivity Analysis – Sel. Pap. ASCE International Conference Computer Science and Engineering* (pp. 530–538). American Society of Civil Engineers (ASCE). <https://doi.org/10.1061/9780784485224.064>
- He, Z., Li, S., Song, Y., & Cai, Z. (2024). Towards building condition-based cross-modality intention-aware human-AI cooperation under VR environment. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642360>
- He, Z., Song, Y., Zhou, S., & Cai, Z. (2023). Interaction of thoughts: Towards mediating task assignment in human-AI cooperation with a capability-aware shared mental model. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3580983>
- Heinzl, B., Silvina, A., Krause, F., Schwarz, N., Kurniawan, K., Kiesling, E., Pichler, M., & Moser, B. (2024). Towards integrating knowledge graphs into process-oriented human-AI collaboration in industry. In P. Bludau, R. Ramler, D. Winkler, & J. Bergmann (Eds.), *Lecture Notes in Business Information Processing* (Vol. 505, pp. 76–87). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-56281-5\\_5](https://doi.org/10.1007/978-3-031-56281-5_5)
- Hemmer, P., Schellhammer, S., Vössing, M., Jakubik, J., & Satzger, G. (2022). Forming effective human-AI teams: Building machine learning models that complement the capabilities of multiple experts. In L. De Raedt & L. De Raedt (Eds.), *IJCAI Int. Joint Conf. Artif. Intell.* (pp. 2478–2484). International Joint Conferences on Artificial Intelligence.
- Hemmer, P., Westphal, M., Schemmer, M., Vetter, S., Vössing, M., & Satzger, G. (2023). Human-AI collaboration: The effect of AI delegation on human task performance and task satisfaction. In *Proceedings of the 28th International Conference on Intelligent User Interfaces (IUI '23)* (pp. 453–463). Association for Computing Machinery. <https://doi.org/10.1145/3581641.3584052>
- Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *The Behavioral and Brain Sciences*, 33(2–3), 61–83. <https://doi.org/10.1017/S0140525X0999152X>
- Heyder, T., Passlack, N., & Posegga, O. (2023). Ethical management of human-AI interaction: Theory development review. *The Journal of Strategic Information Systems*, 32(3), 101772. <https://doi.org/10.1016/j.jsis.2023.101772>
- Heyman, J. L., Rick, S. R., Giacomelli, G., Wen, H., Laubacher, R., Taubenslag, N., Knicker, M., Jeddi, Y., Ragupathy, P., Curhan, J., & Malone, T. (2024). Supermind ideator: How scaffolding human-AI collaboration can increase creativity. In *Proceedings of the ACM Collective Intelligence Conference (CI '24)* (pp. 18–28). Association for Computing Machinery. <https://doi.org/10.1145/3643562.3672611>
- Hinsen, S., Hofmann, P., Jöhnk, J., & Urbach, N. (2022). How can organizations design purposeful human-AI interactions: A practical perspective from existing use cases and interviews. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (Vol. 2022, pp. 196–205). IEEE Computer Society.
- Hirzle, T., Müller, F., Draxler, F., Schmitz, M., Knierim, P., & Hornbæk, K. (2023). When XR and AI meet – A scoping review on extended reality and artificial intelligence. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1–45).
- Hitsuwari, J., Ueda, Y., Yun, W., & Nomura, M. (2023). Does human-AI collaboration lead to more creative art? Aesthetic evaluation of human-made and AI-generated haiku poetry. *Computers in Human Behavior*, 139, 107502. <https://doi.org/10.1016/j.chb.2022.107502>
- Hobbs, K. L. & Li, B. (2024). Safety, trust, and ethics considerations for human-AI teaming in aerospace control. In *AIAA SciTech Forum Expos*. American Institute of Aeronautics and Astronautics Inc, AIAA. <https://doi.org/10.2514/6.2024-2583>
- Hoch, T., Heinzl, B., Czech, G., Khan, M., Waibel, P., Bachhofner, S., Kiesling, E., & Moser, B. (2022). Teaming.AI: Enabling human-AI teaming intelligence in manufacturing. In M. Zelm, A. Boza, R.-D. Leon, & R. Rodriguez-Rodriguez (Eds.), *CEUR Workshop Proceeding* (Vol. 3214). CEUR-WS.
- Hoffman, R. R., Mueller, S. T., Klein, G., & Litman, J. (2023). Measures for explainable AI: Explanation goodness, user satisfaction, mental models, curiosity, trust, and human-AI performance. *Frontiers in Computer Science*, 5, 1096257. <https://doi.org/10.3389/fcomp.2023.1096257>
- Hofmann, Y. & Preiß, C. (2023). Say the image, don't make it: Empowering human-AI co-creation through the interactive installation wishing well. In *AI in Mus.: Reflect., Perspect. and Appl.* (pp. 245–255). Transcript-Verlag.
- Hohenstein, J., Larson, L. E., Hou, Y. T.-Y., Harris, A. M., Schecter, A., DeChurch, L., Contractor, N., & Jung, M. F. (2022). Vero: A method for remotely studying human-AI collaboration. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (Vol. 2022, pp. 254–263). IEEE Computer Society.
- Hois, J., Theofanous-Fuelbier, D., & Junk, A. J. (2019). How to achieve explainability and transparency in human AI interaction. In C. Stephanidis (Ed.), *Communications in computer and information science* (Vol. 1033, pp. 177–183). Springer Verlag. [https://doi.org/10.1007/978-3-030-23528-4\\_25](https://doi.org/10.1007/978-3-030-23528-4_25)
- Holder, E., Huang, L., Chiou, E., Jeon, M., & Lyons, J. B. (2021). Designing for bi-directional transparency in human-AI-robot-teaming. In *Proceeding Hum. Factors Ergon Soc* (Vol. 65, pp. 57–61). SAGE Publications Inc. <https://doi.org/10.1177/1071181321651052>
- Holstein, K. & Aleven, V. (2022). Designing for human-AI complementarity in K-12 education. *AI Magazine*, 43(2), 239–248. <https://doi.org/10.1002/aaai.12058>
- Holstein, K., Aleven, V., & Rummel, N. (2020). A conceptual framework for human-AI hybrid adaptivity in education. In I. I. Bittencourt, M. Cukurova, R. Luckin, K. Muldner, & E. Millán (Eds.), *Lecture Notes in Computer Science LNAI* (Vol. 12163, pp. 240–254). Springer. [https://doi.org/10.1007/978-3-030-52237-7\\_20](https://doi.org/10.1007/978-3-030-52237-7_20)
- Holstein, K., De-Arteaga, M., Tumati, L., & Cheng, Y. (2023). Toward supporting perceptual complementarity in human-AI collaboration via reflection on unobservables. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW1), 1–20. <https://doi.org/10.1145/3579628>
- Holter, S. & El-Assady, M. (2024). Deconstructing human-AI collaboration: Agency, interaction, and adaptation. *Computer Graphics Forum*, 43(3), e15107. <https://doi.org/10.1111/cgf.15107>
- Holtzblatt, K., Burns Wendell, J., & Wood, S. (2005). *Rapid contextual design. A how-to guide to key techniques for user-centered design*. Morgan Kaufmann Publishers. <https://doi.org/10.1016/B978-0-12-354051-5.X5000-9>
- Holzinger, A. & Müller, H. (2021). Toward human-AI interfaces to support explainability and causability in medical AI. *Computer Magazine*, 54(10), 78–86. <https://doi.org/10.1109/MC.2021.3092610>
- Hong, J., Maciejewski, R., Trubuil, A., & Isenberg, T. (2024). Visualizing and comparing machine learning predictions to improve human-AI teaming on the example of cell lineage. *IEEE Transactions on Visualization and Computer Graphics*, 30(4), 1956–1969. <https://doi.org/10.1109/TVCG.2023.3302308>
- Hong, M.-H., Marsh, L. A., Feuston, J. L., Ruppert, J., Brubaker, J. R., & Szafir, D. A. (2022). Scholastic: Graphical human-AI collaboration for inductive and interpretive text analysis. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology (UIST '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3526113.3545681>
- Hong, X., Guan, S.-U., Wong, P. W. H., Xue, N., Man, K. L., & Liu, D. (2021). Can AI teach humans? Humans AI collaboration for lifelong machine learning. In *ACM Int. Conf. Proceeding Ser.* (pp. 427–432). Association for Computing Machinery. <https://doi.org/10.1145/3478905.3478992>
- Hou, K., Hou, T., & Cai, L. (2023). Exploring trust in human-AI collaboration in the context of multiplayer online games. *Systems*, 11(5), 217. <https://doi.org/10.3390/systems11050217>

- Hou, M., Banbury, S., Cain, B., Fang, S., Willoughby, H., Foley, L., Tunstel, E., & Rudas, I. J. (2025). IMPACTS homeostasis trust management system: Optimizing trust in human-AI teams. *ACM Computing Surveys*, 57(6), 1–24. <https://doi.org/10.1145/3649446>
- Hu, H. & Sadigh, D. (2023). Language instructed reinforcement learning for human-AI coordination. In A. Krause, E. Brunskill, K. Cho, B. Engelhardt, S. Sabato, & J. Scarlett (Eds.), *Proceeding Mach. Learn. Res.* (Vol. 202, pp. 13584–13598), ML Research Press.
- Hu, M., Zhang, G., Chong, L., Cagan, J., & Goucher-Lambert, K. (2024). How being outvoted by AI teammates impacts human-AI collaboration. *International Journal of Human-Computer Interaction*, 41(7), 4049–4066. <https://doi.org/10.1080/10447318.2024.2345980>
- Hu, W. (2024). DSNL in architecture – A deep learning approach to deciphering architectural sketches and facilitating human-AI interaction. In N. Gardner, C. M. Herr, L. Wang, H. Toshiki, & S. A. Khan (Eds.), *Proceeding Int. Conf. Comput.-Aided Architect. Des. Res. Asia* (Vol. 1, pp. 119–128). The Association for Computer-Aided Architectural Design Research in Asia.
- Hu, Z., Liu, H., Xiong, Y., Wang, L., Wu, R., Guan, K., Hu, Y., Lyu, T., & Fan, C. (2024). Promoting human-AI interaction makes a better adoption of deep reinforcement learning: A real-world application in game industry. *Multimedia Tools and Applications*, 83(2), 6161–6182. <https://doi.org/10.1007/s11042-023-15361-6>
- Huang, C.-Z. A., Koops, H. V., Newton-Rex, E., Dinculescu, M., & Cai, C. J. (2020). AI song contest: Human-AI co-creation in songwriting. In J. Cumming, J. H. Lee, B. McFee, M. Schedl, J. Devaney, J. Devaney, C. McKay, E. Zangerle, & T. de Reuse (Eds.), *Proceeding Int. Soc. Music Inf. Retr. Conf., ISMIR* (pp. 846–852). International Society for Music Information Retrieval.
- Huang, H., Chen, Y.-Y., Kuo, N.-L., & Hung, M.-J. (2024). More than an IT system in the government: The work divide challenges in human-AI coworking context. In *Proceedings of the 25th Annual International Conference on Digital Government Research (dgo '24)* (pp. 29–41). Association for Computing Machinery. <https://doi.org/10.1145/3657054.3657058>
- Huang, J. Z., Wood, R., Chhabria, H., & Jain, D. (2024). A human-AI collaborative approach for designing sound awareness systems. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642062>
- Huang, Q., Li, Z., Xing, Z., Zuo, Z., Peng, X., Xu, X., & Lu, Q. (2024). Answering uncertain, under-specified API queries assisted by knowledge-aware human-AI dialogue. *IEEE Transactions on Software Engineering*, 50(2), 280–295. <https://doi.org/10.1109/TSE.2023.3346954>
- Huang, Y. & Xiong, D. (2024). CBBQ: A Chinese bias benchmark dataset curated with human-AI collaboration for large language models. In N. Calzolari, M.-Y. Kan, V. Hoste, A. Lenci, S. Sakti, & N. Xue (Eds.), *Jt. Int. Conf. Comput. Linguist., Lang. Resour. Eval., LREC-COLING—Main Conf. Proceeding* (pp. 2917–2929). European Language Resources Association (ELRA).
- Hughes, A. L., Stephens, K. K., Peterson, S., Purohit, H., Harris, A. G., Senarath, Y., Jarvis, S. A., Montagnolo, C. E., & Nader, K. (2022). Human-AI teaming for COVID-19 response: A practice & research collaboration case study. In *Proceeding Int. ISCRAM Conf.* (Vol. 2022, pp. 1048–1057). Information Systems for Crisis Response and Management, ISCRAM.
- Hussain, M., Iacovides, I., Lawton, T., Sharma, V., Porter, Z., Cunningham, A., Habli, I., Hickey, S., Jia, Y., Morgan, P., & Wong, N. L. (2024). Development and translation of human-AI interaction models into working prototypes for clinical decision-making. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference (DIS '24)* (pp. 1607–1619). Association for Computing Machinery. <https://doi.org/10.1145/3643834.3660697>
- Hwang, A. H.-C., Adler, D., Friedenberg, M., & Yang, Q. (2024). Societal-scale human-AI interaction design? How hospitals and companies are integrating pervasive sensing into mental healthcare. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642793>
- Hwang, A. H.-C. & Won, A. S. (2022). AI in your mind: Counterbalancing perceived agency and experience in human-AI interaction. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems (CHI EA '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491101.3519833>
- Hüllmann, J. A., Precht, H., & Wübke, C. (2023). Configurations of human-AI work in agriculture. In A. Stein, C. Hoffmann, A. Ruckelshausen, T. Steckel, F. Helga, & H. Muller (Eds.), *Lect. Notes Informatics (LNI), Proceeding—Series Ges. Inform. (GI)* (Vol. P-330, pp. 363–368). Gesellschaft für Informatik (GI).
- Ilapakurti, A., Kedari, S., Vuppapapati, R., Kedari, S., Vuppapapati, J. S., & Vuppapapati, C. (2019). Human-AI symbiosis: Decode climate change to prevent heat-related mortalities and to protect our most vulnerable population. In M. Qiu (Ed.), *Proceeding—IEEE Int. Conf. Comput. Sci. Eng. IEEE Int. Conf. Embed. Ubiquitous Comput., CSE/EUC* (pp. 331–338). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/CSE/EUC.2019.00070>
- Inkpen, K. (2024). Achievement unlocked: The future of human-AI experiences. In *Proceedings of the 2024 International Conference on Advanced Visual Interfaces (AVI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3656650.3660544>
- Inkpen, K., Chappidi, S., Mallari, K., Nushi, B., Ramesh, D., Michelucci, P., Mandava, V., Vepřek, L. H., & Quinn, G. (2023). Advancing human-AI complementarity: The impact of user expertise and algorithmic tuning on joint decision making. *ACM Transactions on Computer-Human Interaction*, 30(5), 1–29. <https://doi.org/10.1145/3534561>
- Introzzi, L., Zonca, J., Cabitza, F., Cherubini, P., & Reverberi, C. (2024). Enhancing human-AI collaboration: The case of colonoscopy. *Digestive and Liver Disease: Official Journal of the Italian Society of Gastroenterology and the Italian Association for the Study of the Liver*, 56(7), 1131–1139. <https://doi.org/10.1016/j.dld.2023.10.018>
- Jackson Bertón, M. (2021). Text and data mining exception in South America: A way to foster AI development in the region. *GRUR International*, 70(12), 1145–1157. <https://doi.org/10.1093/grurint/ikab081>
- Jacobsen, R. M., Bysted, L. B. L., Johansen, P. S., Papachristos, E., & Skov, M. B. (2020). Perceived and measured task effectiveness in human-AI collaboration. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems (CHI EA '20)* (pp. 1–9). Association for Computing Machinery. <https://doi.org/10.1145/3334480.3383104>
- Jain, R., Garg, N., & Khara, S. N. (2023). Effective human-AI work design for collaborative decision-making. *Kybernetes*, 52(11), 5017–5040. <https://doi.org/10.1108/K-04-2022-0548>
- Jakubik, J., Schöffner, J., Hoge, V., Vössing, M., & Köhl, N. (2023). An empirical evaluation of predicted outcomes as explanations in human-AI decision-making. In I. Koprinka, P. Mignone, R. Guidotti, S. Jaroszewicz, H. Fröning, F. Gullo, P. M. Ferreira, D. Roqueiro, G. Ceddia, S. Nowacznyk, J. Gama, R. Ribeiro, R. Gavalda, E. Masciari, Z. Ras, E. Ritacco, F. Naretto, A. Theissler, P. Biecek, W. Verbeke, G. Schiele, F. Pernkopf, M. Blott, I. Bordino, I. L. Danesi, G. Ponti, L. Severini, A. Appice, G. Andresini, I. Medeiros, G. Graça, L. Cooper, N. Ghazaleh, J. Richiardi, D. Saldana, K. Sechidis, A. Canakoglu, S. Pido, P. Pinoli, A. Bifet, & S. Pashami (Eds.), *Communications in computer and information science, CCIS* (Vol. 1752, pp. 353–368). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-23618-1\\_24](https://doi.org/10.1007/978-3-031-23618-1_24)
- Jang, S. & Nam, K.-Y. (2022). Utilization of speculative design for designing human-AI interactions. *Archives of Design Research*, 35(2), 57–71. <https://doi.org/10.15187/adr.2022.05.35.2.57>
- Jarrah, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586. <https://doi.org/10.1016/j.bushor.2018.03.007>
- Jaszcz, A., Prokop, K., Polap, D., Srivastava, G., & Lin, J. C. (2023). Human-AI collaboration to increase the perception of VR. In L. Rutkowski, L. Rutkowski, R. Scherer, M. Korytkowski, W. Pedrycz, R. Tadeusiewicz, & J. M. Zurada (Eds.), *Lecture Notes in Computer Science LNAI* (Vol. 13588, pp. 51–60). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-23492-7\\_5](https://doi.org/10.1007/978-3-031-23492-7_5)



- Jiang, J., Karran, A. J., Coursaris, C. K., Léger, P.-M., & Beringer, J. (2023). A situation awareness perspective on human-AI interaction: Tensions and opportunities. *International Journal of Human-Computer Interaction*, 39(9), 1789–1806. <https://doi.org/10.1080/10447318.2022.2093863>
- Jiang, J. A., Wade, K., Fiesler, C., & Brubaker, J. R. (2021). Supporting serendipity: Opportunities and challenges for human-AI collaboration in qualitative analysis. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1), 1–23. <https://doi.org/10.1145/3449168>
- Jiang, L., Ahmadon, M. A. B., & Yamaguchi, S. (2024). Advancing synergyAI: Enhancing explainability and decision tree optimization in human-AI pair programming. In *Dig. Tech. Pap. IEEE Int. Conf. Consum. Electron.* Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICCE59016.2024.10444384>
- Jiang, L., Bin Ahmadon, M. A., Zhang, D., Fukada, T., & Yamaguchi, S. (2023). SynergyAI: An human-AI pair programming design tool based on program Net. In *Int. Conf. Inf. Educ. Technol., ICIET* (pp. 210–214). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICIET56899.2023.10111108>
- Jiang, N., Liu, X., Liu, H., Lim, E. T. K., Tan, C.-W., & Gu, J. (2023). Beyond AI-powered context-aware services: The role of human-AI collaboration. *Industrial Management & Data Systems*, 123(11), 2771–2802. <https://doi.org/10.1108/IMDS-03-2022-0152>
- Jiang, Q., Zhang, Y., & Pian, W. (2022). Chatbot as an emergency exist: Mediated empathy for resilience via human-AI interaction during the COVID-19 pandemic. *Information Processing & Management*, 59(6), 103074. <https://doi.org/10.1016/j.ipm.2022.103074>
- Jiang, T., Sun, Z., Fu, S., & Lv, Y. (2024). Human-AI interaction research agenda: A user-centered perspective. *Data and Information Management*, 8(4), 100078. <https://doi.org/10.1016/j.dim.2024.100078>
- Jin, S. V. & Youn, S. (2023). Social presence and imagery processing as predictors of chatbot continuance intention in human-AI-interaction. *International Journal of Human-Computer Interaction*, 39(9), 1874–1886. <https://doi.org/10.1080/10447318.2022.2129277>
- Jones, B. T. & Tanimoto, S. L. (2018). Searching over search trees for human-AI collaboration in exploratory problem solving: A case study in Algebra. In C. Kelleher, G. Engels, J. P. Fernandes, J. Cunha, & J. Mendes (Eds.), *Proceeding of IEEE Symp. Vis. Lang. Hum.-Cent. Comput., VL/HCC* (Vol. 2018, pp. 33–37). IEEE Computer Society. <https://doi.org/10.1109/VLHCC.2018.8506580>
- Jorge, C. C., Jonker, C. M., & Tielman, M. L. (2023). Artificial trust for decision-making in human-AI teamwork: Steps and challenges. In P. K. Murukannaiah & T. Hirzle (Eds.), *CEUR Workshop Proceeding* (Vol. 3456, pp. 150–156). CEUR-WS.
- Judkins, J. T., Hwang, Y., & Kim, S. (2024). Human-AI interaction: Augmenting decision-making for IT leader's project selection. *Information Development*. <https://doi.org/10.1177/02666669241249744>
- Kaartemo, V. & Helkkula, A. (2024). Human-AI resource relations in value cocreation in service ecosystems. *Journal of Service Management*, 36(2), 291–306. <https://doi.org/10.1108/JOSM-03-2023-0104>
- Kambhampati, S., Sreedharan, S., Verma, M., Zha, Y., & Guan, L. (2022). Symbols as a lingua franca for bridging human-AI chasm for explainable and advisable AI systems. In *Proceeding AAAI Conf. Artif. Intell., AAAI* (Vol. 36, pp. 12262–12267). Association for the Advancement of Artificial Intelligence.
- Kamboj, P., Banerjee, A., & Gupta, S. K. (2024). Expert knowledge driven human-AI collaboration for medical imaging: A study on epileptic seizure onset zone identification. *IEEE Transactions on Artificial Intelligence*, 5(10), 5352–5368. <https://doi.org/10.1109/TAI.2024.3396421>
- Kanda, T., Ito, H., & Morishima, A. (2022). Efficient evaluation of AI workers for the human + AI crowd task assignment. In S. Tsumoto, Y. Ohsawa, L. Chen, D. Van den Poel, X. Hu, Y. Motomura, T. Takagi, L. Wu, Y. Xie, A. Abe, & V. Raghavan (Eds.), *Proceeding—IEEE International Conference on Big Data* (pp. 3995–4001). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/BigData55660.2022.10020844>
- Kang, H. & Lou, C. (2022). AI agency vs. human agency: Understanding human-AI interactions on TikTok and their implications for user engagement. *Journal of Computer-Mediated Communication*, 27(5), zmac014. <https://doi.org/10.1093/jcmc/zmac014>
- Kannally, C. T., Smith, J. R., & Ijtsma, M. (2023). Human-AI teaming in the automotive and mobility industry: Guiding design to support joint activity. In *Proceeding Hum. Factors Ergon Soc.* (Vol. 67, No. 1, pp. 111–116). SAGE Publications Inc. <https://doi.org/10.1177/21695067231192223>
- Karakose, T., Demirkol, M., Aslan, N., Köse, H., & Yirci, R. (2023). A conversation with ChatGPT about the impact of the COVID-19 pandemic on education: Comparative review based on human-AI collaboration. *Educational Process International Journal*, 12(3), 7–25. <https://doi.org/10.22521/edupij.2023.123.1>
- Karakose, T., Demirkol, M., Yirci, R., Polat, H., Ozdemir, T. Y., & Tülübaşı, T. (2023). A conversation with ChatGPT about digital leadership and technology integration: Comparative analysis based on human-AI collaboration. *Administrative Sciences*, 13(7), 157. <https://doi.org/10.3390/admsci13070157>
- Karimi, P., Rezwana, J., Siddiqui, S., Maher, M. L., & Dehbozorgi, N. (2020). Creative sketching partner: An analysis of human-AI co-creativity. In *Proceedings of the 25th International Conference on Intelligent User Interfaces (IUI '20)* (pp. 221–230). Association for Computing Machinery. <https://doi.org/10.1145/3377325.3377522>
- Kariyawasam, H., Niwarthana, A., Palmer, A., Kay, J., & Withana, A. (2024). Appropriate incongruity driven human-AI collaborative tool to assist novices in humorous content generation. In *Proceedings of the 29th International Conference on Intelligent User Interfaces (IUI '24)* (pp. 650–659). Association for Computing Machinery. <https://doi.org/10.1145/3640543.3645161>
- Karumbaiah, S., Liu, P., Maksimova, A., De Vylder, L., Rummel, N., & Alevén, V. (2023). Multimodal analytics for collaborative teacher reflection of human-AI hybrid teaching: Design opportunities and constraints. In O. Viberg, I. Jivet, P. J. Muñoz-Merino, M. Perifanou, & T. Papathoma (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 14200, pp. 580–585). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-42682-7\\_45](https://doi.org/10.1007/978-3-031-42682-7_45)
- Kawakami, A., Sivaraman, V., Cheng, H.-F., Stapleton, L., Cheng, Y., Qing, D., Perer, A., Wu, Z. S., Zhu, H., & Holstein, K. (2022). Improving human-AI partnerships in child welfare: Understanding worker practices, challenges, and desires for algorithmic decision support. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3517439>
- Khadpe, P., Krishna, R., Fei-Fei, L., Hancock, J. T., & Bernstein, M. S. (2020). Conceptual metaphors impact perceptions of human-AI collaboration. *Proceedings of the ACM on Human-Computer Interaction*, 4(CSCW2), 1–26. <https://doi.org/10.1145/3415234>
- Khan, S., Kakkis, P., & Goucher-Lambert, K. (2023). How does agency impact human-AI collaborative design space exploration? A case study on ship design with deep generative models. In *Proceeding ASME Des. Eng. Tech. Conf.* (Vol. 3B). American Society of Mechanical Engineers (ASME). <https://doi.org/10.1115/DETC2023-112570>
- Khushk, A., Zhiying, L., Yi, X., & Zhang, X. (2024). Navigating human-AI dynamics: Implications for organizational performance (SLR). *International Journal of Organizational Analysis*. <https://doi.org/10.1108/IJOA-04-2024-4456>
- Kiemde, S. M. A. & Kora, A. D. (2020). The challenges facing the development of AI in Africa. In *2020 IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation (ICATMRI)* (pp. 1–6). IEEE.
- Kilic, K., Weck, S., Kampik, T., & Lindgren, H. (2023). Argument-based human-AI collaboration for supporting behavior change to improve health. *Frontiers in Artificial Intelligence*, 6, 1069455. <https://doi.org/10.3389/frai.2023.1069455>
- Kim, E., Hong, J., Lee, H., & Ko, M. (2022). Colorbo: Envisioned mandala coloring through human-AI collaboration. In *Proceedings of the 27th International Conference on Intelligent User Interfaces (IUI '22)* (pp. 15–26). Association for Computing Machinery. <https://doi.org/10.1145/3490099.3511135>
- Kim, J., Maher, M. L., & Siddiqui, S. (2021). Collaborative ideation partner: Design ideation in human-AI co-creativity. In H. P. Silva,

- L. Constantine, & A. Holzinger (Eds.), *International Conference on Computer-Human Interaction Research and Applications, CHIRA—Proceedings* (Vol. 2021, pp. 123–130). Science and Technology Publications, Ltd.
- Kim, J. C., Laine, T. H., & Åhlund, C. (2021). Multimodal interaction systems based on Internet of Things and augmented reality: A systematic literature review. *Applied Sciences*, 11(4), 1738. <https://doi.org/10.3390/app11041738>
- Kim, M. K. & Trewitt, E. (2022). SatisfAI: A serious tabletop game to reveal human-AI interaction dynamics. In R. A. Sottilare & J. Schwarz (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 13332, pp. 174–189). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-05887-5\\_13](https://doi.org/10.1007/978-3-031-05887-5_13)
- Kim, S. S. Y., Watkins, E. A., Russakovsky, O., Fong, R., & Monroy-Hernández, A. (2023). “Help me help the AI”: Understanding how explainability can support human-AI interaction. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3581001>
- Kim, T., Shin, D., Kim, Y.-H., & Hong, H. (2024). DiaryMate: Understanding user perceptions and experience in human-AI collaboration for personal journaling. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642693>
- Kitchenham, B. & Brereton, P. (2013). A systematic review of systematic review process research in software engineering. *Information and Software Technology*, 55(12), 2049–2075. <https://doi.org/10.1016/j.infsof.2013.07.010>
- Kitchenham, B. & Charters, S. (2007). *Guidelines for performing systematic literature reviews in software engineering*.
- Kiyemba, D. M., Marwad, J., Carter, E. J., & Norton, A. (2024). Evaluation tools for human-AI interactions involving older adults with mild cognitive impairments. In *Proceedings of the 2024 ACM/IEEE International Conference on Human-Robot Interaction (HRI '24)* (pp. 915–918). Association for Computing Machinery. <https://doi.org/10.1145/3610977.3637474>
- Kleanthous, S. (2024). Human-AI teaming: Following the IMOI framework. In H. Degen & S. Ntoa (Eds.), *Lecture Notes in Computer Science, LNAI* (Vol. 14735, pp. 387–406). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-60611-3\\_27](https://doi.org/10.1007/978-3-031-60611-3_27)
- Klein, G., Hoffman, R. R., Clancey, W. J., Mueller, S. T., Jentsch, F., & Jalaeian, M. (2023). “Minimum necessary rigor” in empirically evaluating human-AI work systems. *AI Magazine*, 44(3), 274–281. <https://doi.org/10.1002/aaai.12108>
- Klock, A. C. T., Gasparini, I., Pimenta, M. S., & Hamari, J. (2020). Tailored gamification: A review of literature. *International Journal of Human-Computer Studies*, 144, 102495. <https://doi.org/10.1016/j.ijhcs.2020.102495>
- Knijnenburg, B. P., Reijmer, N. J. M., & Willemsen, M. C. (2011). Each to his own: How different users call for different interaction methods in recommender systems. In *Proceedings of the Fifth ACM Conference on Recommender Systems* (pp. 141–148). ACM. <https://doi.org/10.1145/2043932.204396>
- Knowles, A. M. (2022). Human-AI collaborative writing: Sharing the rhetorical task load. In *IEEE Int. Prof. Commun. Conf.* (Vol. 2022, pp. 257–261). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ProComm53155.2022.00053>
- Kobayashi, M., Wakabayashi, K., & Morishima, A. (2021). Human + AI crowd task assignment considering result quality requirements. In E. Kamar & K. Luther (Eds.), *Proceeding AAAI Conference on Human Computer Crowdsourcing* (Vol. 9, pp. 97–107). Association for the Advancement of Artificial Intelligence. <https://doi.org/10.1609/hcomp.v9i1.18943>
- Koehl, D. & Vangsness, L. (2023). Measuring latent trust patterns in large language models in the context of human-AI teaming. In *Proceeding Hum. Factors Ergon Soc.* (Vol. 67, No. 1, pp. 504–511). SAGE Publications Inc. <https://doi.org/10.1177/21695067231192869>
- Kolbjørnsrud, V. (2024). Designing the intelligent organization: Six principles for human-AI collaboration. *California Management Review*, 66(2), 44–64. <https://doi.org/10.1177/00081256231211020>
- Kongmanee, J., Chung, M.-H., Luna, A., Zhan, L., Jerath, K., Raman, A., & Chignell, M. H. (2024). A human-AI interaction dashboard for detecting potentially malicious emails. In M. Hou, T. H. Falk, A. Mohammadi, A. Guerrieri, & D. Kaber (Eds.), *IEEE Int. Conf. Hum.-Mach. Syst., ICHMS*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICHMS59971.2024.10555737>
- Kou, Z., Shang, L., Zhang, Y., Yue, Z., Zeng, H., & Wang, D. (2022). Crowd, expert & AI: A human-AI interactive approach towards natural language explanation based COVID-19 misinformation detection. In L. De Raedt & L. De Raedt (Eds.), *IJCAI Int. Joint Conf. Artif. Intell.* (pp. 5087–5093). International Joint Conferences on Artificial Intelligence.
- Koçak, Ö., Park, S., & Puranam, P. (2022). Ambiguity can compensate for semantic differences in human-AI communication. *Computers in Human Behavior Reports*, 6, 100200. <https://doi.org/10.1016/j.chbr.2022.100200>
- Krakowski, I., Kim, J., Cai, Z. R., Daneshjou, R., Lapins, J., Eriksson, H., Lykou, A., & Linos, E. (2024). Human-AI interaction in skin cancer diagnosis: A systematic review and meta-analysis. *NPJ Digital Medicine*, 7(1), 78. <https://doi.org/10.1038/s41746-024-01031-w>
- Kraus, M., Riekenbrauck, R., & Minker, W. (2023). Development of a trust-aware user simulator for statistical proactive dialog modeling in human-AI teams. In *Adjunct Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization (UMAP '23 Adjunct)* (pp. 38–43). Association for Computing Machinery. <https://doi.org/10.1145/3563359.3597403>
- Krueger, J. & Roberts, T. (2024). Real feeling and fictional time in human-AI interactions. *Topoi*, 43(3), 783–794. <https://doi.org/10.1007/s11245-024-10046-7>
- Kuang, E. (2023). Crafting human-AI collaborative analysis for user experience evaluation. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544549.3577042>
- Kuang, E., Soure, E. J., Fan, M., Zhao, J., & Shinohara, K. (2023). Collaboration with conversational AI assistants for UX evaluation: Questions and how to ask them (voice vs. text). In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. ACM. <https://doi.org/10.1145/3544548.3581247>
- Kwon, N., Sun, T. S., Gao, Y., Zhao, L., Wang, X., Kim, J., & Hong, S. R. (2024). 3DPFIX: Improving remote novices' 3D printing troubleshooting through human-AI collaboration design. *Proceedings of the ACM on Human-Computer Interaction*, 8(CSCW1), 1–33. <https://doi.org/10.1145/3637288>
- Kwon, S., Yoo, D. W., & Kang, Y. (2024). Spiritual AI: Exploring the possibilities of a human-AI interaction beyond productive goals. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3650743>
- La Sala, A., Fuller, R., Riolfi, L., & Temperini, V. (2024). The rise of hybrids: Plastic knowledge in human-AI interaction. *Journal of Knowledge Management*, 28(10), 3023–3045. <https://doi.org/10.1108/JKM-10-2023-1024>
- Lai, V., Carton, S., Bhatnagar, R., Liao, Q. V., Zhang, Y., & Tan, C. (2022). Human-AI collaboration via conditional delegation: A case study of content moderation. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3501999>
- Lai, V., Chen, C., Smith-Renner, A., Liao, Q. V., & Tan, C. (2023). Towards a science of human-AI decision making: An overview of design space in empirical human-subject studies. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (FAccT '23)* (pp. 1369–1385). Association for Computing Machinery. <https://doi.org/10.1145/3593013.3594087>
- Lai, Y., Kankanalli, A., & Ong, D. C. (2021). Human-AI collaboration in healthcare: A review and research agenda. In T. X. Bui (Ed.),



- Proceedings Annual Hawaii International Conference on System Science* (Vol. 2020, pp. 390–399). IEEE Computer Society.
- Laney, M. & Dewan, P. (2024). Human-AI collaboration in a student discussion forum. In *Companion Proceedings of the 29th International Conference on Intelligent User Interfaces (IUI '24 Companion)* (pp. 74–77). Association for Computing Machinery. <https://doi.org/10.1145/3640544.3645215>
- Langer, M., Hunsicker, T., Feldkamp, T., König, C. J., & Grgić-Hlača, N. (2022). Look! It's a computer program! It's an algorithm! It's AI!": Does terminology affect human perceptions and evaluations of algorithmic decision-making systems?. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1–28).
- Largent, M., Jensen, G., & Law, R. (2018). The design for maritime singularity: Exploration of human/AI teaming and organizational carrying capacity for the U.S. Navy. In *Springer Proceeding Complex* (pp. 368–379). Springer. [https://doi.org/10.1007/978-3-319-96661-8\\_38](https://doi.org/10.1007/978-3-319-96661-8_38)
- Lauer, T. & Wieland, S. (2021). Human-AI-collaboration in the context of information asymmetry—A behavioral analysis of demand forecasting. In T. Z. Ahram, W. Karwowski, & J. Kalra (Eds.), *Lect. Notes Networks Syst.* (Vol. 271, pp. 3–13). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-80624-8\\_1](https://doi.org/10.1007/978-3-030-80624-8_1)
- Lawton, T., Grace, K., & Ibarrola, F. J. (2023). When is a tool a tool? User perceptions of system agency in human-AI co-creative drawing. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference (DIS '23)* (pp. 1978–1996). Association for Computing Machinery. <https://doi.org/10.1145/3563657.3595977>
- Le Guillou, M., Prévot, L., & Berberian, B. (2023). Bringing together ergonomic concepts and cognitive mechanisms for human-AI agents cooperation. *International Journal of Human-Computer Interaction*, 39(9), 1827–1840. <https://doi.org/10.1080/10447318.2022.2129741>
- Lee, J. H., Hong, H., Nam, G., Hwang, E. J., & Park, C. M. (2023). Effect of human-AI interaction on detection of malignant lung nodules on chest radiographs. *Radiology*, 307(5), e222976. <https://doi.org/10.1148/radiol.222976>
- Lee, M., Liang, P., & Yang, Q. (2022). CoAuthor: Designing a human-AI collaborative writing dataset for exploring language model capabilities. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3502030>
- Lee, M. H. & Chew, C. J. (2023). Understanding the effect of counterfactual explanations on trust and reliance on AI for human-AI collaborative clinical decision making. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW2), 1–22. <https://doi.org/10.1145/3610218>
- Lee, M. H., Siewiorek, D. P., Smailagic, A., Bernardino, A., & Bermúdez I Badia, S. (2022). Towards efficient annotations for a human-AI collaborative, clinical decision support system: A case study on physical stroke rehabilitation assessment. In *Proceedings of the 27th International Conference on Intelligent User Interfaces (IUI '22)* (pp. 4–14). Association for Computing Machinery. <https://doi.org/10.1145/3490099.3511112>
- Lee, M. H., Siewiorek, D. P., Smailagic, A., Alexandre, B., & Bermúdez I Badia, S. B. (2021). A human-AI collaborative approach for clinical decision making on rehabilitation assessment. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery. <https://doi.org/10.1145/3411764.3445472>
- Lee, S., Lee, M., & Lee, S. (2023). What if artificial intelligence become completely ambient in our daily lives? Exploring future human-AI interaction through high fidelity illustrations. *International Journal of Human-Computer Interaction*, 39(7), 1371–1389. <https://doi.org/10.1080/10447318.2022.2080155>
- Lee, S., Yu, R., Xie, J., Billah, S. M., & Carroll, J. M. (2022). Opportunities for human-AI collaboration in remote sighted assistance. In *Proceedings of the 27th International Conference on Intelligent User Interfaces (IUI '22)* (pp. 63–78). Association for Computing Machinery. <https://doi.org/10.1145/3490099.3511113>
- Lee, S.-y., Law, M., & Hoffman, G. (2025). When and how to use AI in the design process? Implications for human-AI design collaboration. *International Journal of Human-Computer Interaction*, 41(2), 1569–1584. <https://doi.org/10.1080/10447318.2024.2353451>
- Lee, Y., Chung, J. J. Y., Kim, T. S., Song, J. Y., & Kim, J. (2022). Promptiverse: Scalable generation of scaffolding prompts through human-AI hybrid knowledge graph annotation. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3502087>
- Legaspi, R., Xu, W., Konishi, T., Wada, S., Kobayashi, N., Naruse, Y., & Ishikawa, Y. (2024). The sense of agency in human-AI interactions. *Knowledge-Based Systems*, 286, 111298. <https://doi.org/10.1016/j.knsys.2023.111298>
- Lematta, G. J., Corral, C. C., Buchanan, V., Johnson, C. J., Mudigonda, A., Scholcover, F., Wong, M. E., Ezenyilimba, A., Baeriswyl, M., Kim, J., Holder, E., Chiou, E. K., & Cooke, N. J. (2022). Remote research methods for human-AI-robot teaming. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 32(1), 133–150. <https://doi.org/10.1002/hfm.20929>
- Lemmer, S. J., Guo, A., & Corso, J. J. (2023). Human-centered deferred inference: Measuring user interactions and setting deferral criteria for human-AI teams. In *Proceedings of the 28th International Conference on Intelligent User Interfaces (IUI '23)* (pp. 681–694). Association for Computing Machinery. <https://doi.org/10.1145/3581641.3584092>
- Lemus, H. T., Kumar, A., & Steyvers, M. (2023). How displaying AI confidence affects reliance and hybrid human-AI performance. In P. Lukowicz, S. Mayer, J. Koch, J. Shawe-Taylor, & I. Tiddi (Eds.), *Frontiers in artificial intelligence and applications* (Vol. 368, pp. 234–242). IOS Press BV. <https://doi.org/10.3233/FAIA230087>
- Li, F. & Lu, Y. (2024). Human-AI interaction and ethics of AI: How well are we following the guidelines. In *Proceedings of the Tenth International Symposium of Chinese CHI (Chinese CHI '22)* (pp. 96–104). Association for Computing Machinery. <https://doi.org/10.1145/3565698.3565773>
- Li, H., Wang, Y., & Qu, H. (2024). Where are we so far? Understanding data storytelling tools from the perspective of human-AI collaboration. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642726>
- Li, J., Huang, J., Liu, J., & Zheng, T. (2022). Human-AI cooperation: Modes and their effects on attitudes. *Telematics and Informatics*, 73, 101862. <https://doi.org/10.1016/j.tele.2022.101862>
- Li, J. & Lafond, D. (2023). Hybrid human-AI forecasting for task duration estimation in ship refit. In G. Nicosia, G. Giuffrida, V. Ojha, E. La Malfa, G. La Malfa, P. Pardalos, G. Di Fatta, & R. Umeton (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 13810, pp. 558–572). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-25599-1\\_41](https://doi.org/10.1007/978-3-031-25599-1_41)
- Li, Y., Yin, D., Lafond, A., Ghasemi, C., Diallo, & E., Bertrand. (2024). Integrated human-AI forecasting for preventive maintenance task duration estimation. In G. Nicosia, V. Ojha, E. La Malfa, G. La Malfa, P. M. Pardalos, & R. Umeton (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 14506, pp. 3–18). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-53966-4\\_1](https://doi.org/10.1007/978-3-031-53966-4_1)
- Li, Q., Peng, Z., & Zhou, B. (2022). Efficient learning of safe driving policy via human-AI copilot optimization. In *ICLR—Int. Conf. Learn. Represent.* International Conference on Learning Representations, ICLR.
- Li, T., Vorvoreanu, M., Debellis, D., & Amershi, S. (2023). Assessing human-AI interaction early through factorial surveys: A study on the guidelines for human-AI interaction. *ACM Transactions on Computer-Human Interaction*, 30(5), 1–45. <https://doi.org/10.1145/3511605>
- Li, Y., Karim, M. M., & Qin, R. (2023). A gaze data-based comparative study to build a trustworthy human-AI collaboration in crash anticipation. In H. Wei (Ed.), *Int. Conf. Transp. Dev.: Transp. Saf. Emerg. Technol.—Sel. Pap. Int. Conf. Transp. Dev.* (Vol. 2, pp. 737–748). American Society of Civil Engineers (ASCE). <https://doi.org/10.1061/9780784484883.064>
- Li, Y., Li, Y., Chen, Q., & Chang, Y. (2024). Humans as teammates: The signal of human-AI teaming enhances consumer acceptance of

- chatbots. *International Journal of Information Management*, 76, 102771. <https://doi.org/10.1016/j.ijinfomgt.2024.102771>
- Li, Y., Wu, B., Huang, Y., & Luan, S. (2024). Developing trustworthy artificial intelligence: Insights from research on interpersonal, human-automation, and human-AI trust. *Frontiers in Psychology*, 15, 1382693. <https://doi.org/10.3389/fpsyg.2024.1382693>
- Li, Z., Wang, Y., Wang, W., Greuter, S., & Mueller, F. (2020). Empowering a creative city: Engage citizens in creating street art through human-AI collaboration. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems (CHI EA '20)* (pp. 1–8). Association for Computing Machinery. <https://doi.org/10.1145/3334480.3382976>
- Liang, C., Proft, J., Andersen, E., & Knepper, R. A. (2019). Implicit communication of actionable information in human-AI teams. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)* (pp. 1–13). Association for Computing Machinery. <https://doi.org/10.1145/3290605.3300325>
- Liao, M. & Sundar, S. S. (2021). How should AI systems talk to users when collecting their personal information? Effects of role framing and self-referencing on human-AI interaction. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery. <https://doi.org/10.1145/3411764.3445415>
- Liapis, A., Guckelsberger, C., Zhu, J., Harteveld, C., Kriglstein, S., Denisova, A., Gow, J., & Preuss, M. (2023). Designing for playfulness in human-AI authoring tools. In *Proceedings of the 18th International Conference on the Foundations of Digital Games (FDG '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3582437.3587192>
- Licklider, J. C. R. (1960). Man-computer symbiosis. *IRE Transactions on Human Factors in Electronics*, HFE-1(1), 4–11. <https://doi.org/10.1109/THFE2.1960.4503259>
- Lindner, S. & Schulte, A. (2024). Enhancing tactical military mission execution through human-AI collaboration: A view on air battle management systems. In M. Hou, T. H. Falk, A. Mohammadi, A. Guerrieri, & D. Kaber (Eds.), *IEEE Int. Conf. Hum.-Mach. Syst., ICHMS*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICHMS59971.2024.10555606>
- Linnyk, O. & Teetz, I. (2023). Counteracting the global labor shortage risk through the human-AI collaboration in digital recruiting. *IEEE Technology and Society Magazine*, 42(2), 42–47. <https://doi.org/10.1109/MTS.2023.3277108>
- Liu, A., Guerra, S., Fung, I., Matute, G., Kamar, E., & Lasecki, W. (2020). Towards hybrid human-AI workflows for unknown unknown detection. In *Proceedings of The Web Conference 2020 (WWW '20)* (pp. 2432–2442). Association for Computing Machinery. <https://doi.org/10.1145/3366423.3380306>
- Liu, B. (2021). In AI we trust? Effects of agency locus and transparency on uncertainty reduction in human-AI interaction. *Journal of Computer-Mediated Communication*, 26(6), 384–402. <https://doi.org/10.1093/jcmc/zmab013>
- Liu, H., Lai, V., & Tan, C. (2021). Understanding the effect of out-of-distribution examples and interactive explanations on human-AI decision making. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW2), 1–45. <https://doi.org/10.1145/3479552>
- Liu, J., Ito, S., Ngo, T. M., Lawate, A., Ong, Q. C., Fox, T. E., Chang, S. Y., Phung, D., Nair, E., Palaiyan, M., Joty, S., Abisheganaden, J., Lee, C. P., Lwin, M. O., Theng, Y. L., Ho, M.-H. R., Chia, M., Bojic, I., & Car, J. (2024). A pilot randomised controlled trial exploring the feasibility and efficacy of a human-AI sleep coaching model for improving sleep among university students. *Digital Health*, 10, 20552076241241244. <https://doi.org/10.1177/20552076241241244>
- Liu, J., Yu, C., Gao, J., Xie, Y., Liao, Q., Wu, Y., & Wang, Y. (2024). LLM-powered hierarchical language agent for real-time human-AI coordination. In *Proceedings of the 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS '24)* (pp. 1219–1228). International Foundation for Autonomous Agents and Multiagent Systems.
- Liu, M., Lv, W., Yin, B., Ge, Y., & Wei, W. (2022). The human-AI scoring system: A new method for CT-based assessment of COVID-19 severity. *Technology and Health Care: Official Journal of the European Society for Engineering and Medicine*, 30(1), 1–10. <https://doi.org/10.3233/THC-213199>
- Liu, Y. & Siau, K. L. (2023). Human-AI interaction and AI avatars. In H. Degen, S. Ntoa, & A. Moallem (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 14059, pp. 120–130). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-48057-7\\_8](https://doi.org/10.1007/978-3-031-48057-7_8)
- Liu-Thompkins, Y., Okazaki, S., & Li, H. (2022). Artificial empathy in marketing interactions: Bridging the human-AI gap in affective and social customer experience. *Journal of the Academy of Marketing Science*, 50(6), 1198–1218. <https://doi.org/10.1007/s11747-022-00892-5>
- Lobo, I., Koch, J., Renoux, J., Batina, I., & Prada, R. (2024). When should I lead or follow: Understanding initiative levels in human-AI collaborative gameplay. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference (DIS '24)* (pp. 2037–2056). Association for Computing Machinery. <https://doi.org/10.1145/3643834.3661583>
- Longo, L., Brcic, M., Cabitza, F., Choi, J., Confalonieri, R., Ser, J. D., Guidotti, R., Hayashi, Y., Herrera, F., Holzinger, A., Jiang, R., Khosravi, H., Lecue, F., Malgieri, G., Páez, A., Samek, W., Schneider, J., Speith, T., & Stumpf, S. (2024). Explainable Artificial Intelligence (XAI) 2.0: A manifesto of open challenges and interdisciplinary research directions. *Information Fusion*, 106, 102301. <https://doi.org/10.1016/j.inffus.2024.102301>
- Loo, Y., Gong, C., & Meghjani, M. (2023). A hierarchical approach to population training for human-AI collaboration. In *IJCAI Int. Joint Conf. Artif. Intell.* (Vol. 2023, pp. 3011–3019). International Joint Conferences on Artificial Intelligence.
- Loske, D. & Klumpp, M. (2021a). Human-AI collaboration in route planning: An empirical efficiency-based analysis in retail logistics. *International Journal of Production Economics*, 241, 108236. <https://doi.org/10.1016/j.ijpe.2021.108236>
- Loske, D. & Klumpp, M. (2021b). Intelligent and efficient? An empirical analysis of human-AI collaboration for truck drivers in retail logistics. *The International Journal of Logistics Management*, 32(4), 1356–1383. <https://doi.org/10.1108/IJLM-03-2020-0149>
- Lou, X., Guo, J., Zhang, J., Wang, J., Huang, K., & Du, Y. (2023). PECAN: Leveraging policy ensemble for context-aware zero-shot human-AI coordination. In *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems (AAMAS '23)* (pp. 679–688). International Foundation for Autonomous Agents and Multiagent Systems.
- Lou, Z. & Wei, H. (2023). Enhancing human-AI trust by describing AI decision-making behavior. In R. Song (Ed.), *Proceeding IEEE Int. Conf. Unmanned Syst., ICUS* (pp. 1351–1356). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICUS58632.2023.10318430>
- Lu, F., Xu, Y., Xu, X., Jones, B., & Malamed, L. (2023). Exploring the impact of user and system factors on human-AI interactions in head-worn displays. In G. Bruder, A. H. Olivier, A. Cunningham, E. Y. Peng, J. Grubert, & I. Williams (Eds.), *Proceeding—IEEE Int. Symp. Mixed Augment. Real., ISMAR* (pp. 109–118). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ISMAR59233.2023.00025>
- Lu, Q. & Peng, X. (2024). Differences in knowledge adoption among task types in human-AI collaboration under the chronic disease prevention scenario. In I. Sserwanga, H. Joho, J. Ma, P. Hansen, D. Wu, M. Koizumi, & A. J. Gilliland (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 14598, pp. 213–231). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-57867-0\\_16](https://doi.org/10.1007/978-3-031-57867-0_16)
- Lundberg, J., Arvola, M., & Palmerius, K. L. (2021). Human autonomy in future drone traffic: Joint human-AI control in temporal cognitive work. *Frontiers in Artificial Intelligence*, 4, 704082. <https://doi.org/10.3389/frai.2021.704082>
- Lyons, J. B., Sycara, K., Lewis, M., & Capiola, A. (2021). Human-autonomy teaming: Definitions, debates, and directions. *Frontiers in Psychology*, 12, 589585. <https://doi.org/10.3389/fpsyg.2021.589585>
- Lyu, Y., Wang, X., Lin, R., & Wu, J. (2022). Communication in human-AI co-creation: Perceptual analysis of paintings generated by



- text-to-image system. *Applied Sciences (Switzerland)*, 12(22), 11312. <https://doi.org/10.3390/app122211312>
- Ma, H., Vo, T. V., & Leong, T.-Y. (2023). Human-AI collaborative sub-goal optimization in hierarchical reinforcement learning. In H. Soh, C. Geib, & R. Petrick (Eds.), *Proceeding Inaug. Summer Symp. Ser.* (pp. 86–89). AAAI Press.
- Ma, Q. C., Wu, S. T., & Koedinger, K. (2023). Is AI the better programming partner? Human-human pair programming vs. human-AI pair programming. In S. Moore, J. Stamper, R. Tong, C. Cao, Z. Liu, X. Hu, Y. Lu, J. Liang, H. Khosravi, P. Denny, A. Singh, & C. Brooks (Eds.), *CEUR Workshop Proceeding* (Vol. 3487, pp. 64–77). CEUR-WS.
- Ma, X. & Huo, Y. (2024). Drawing a satisfying picture: An exploratory study of human-AI interaction in AI painting through breakdown-repair communication strategies. *Information Processing & Management*, 61(4), 103755. <https://doi.org/10.1016/j.ipm.2024.103755>
- Maadi, M., Akbarzadeh Khorshidi, H., & Aickelin, U. (2021). A review on human-AI interaction in machine learning and insights for medical applications. *International Journal of Environmental Research and Public Health*, 18(4), 2121. <https://doi.org/10.3390/ijerph18042121>
- Maeda, T. & Quan-Haase, A. (2024). When human-AI interactions become parasocial: Agency and anthropomorphism in affective design. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency (FAccT '24)* (pp. 1068–1077). Association for Computing Machinery. <https://doi.org/10.1145/3630106.3658956>
- Mahmud, B., Hong, G., & Fong, B. (2024). A study of human-AI symbiosis for creative work: Recent developments and future directions in deep learning. *ACM Transactions on Multimedia Computing, Communications, and Applications*, 20(2), 1–21. <https://doi.org/10.1145/3542698>
- Malakis, S., Baumgartner, M., Berzina, N., Laursen, T., Smoker, A., Poti, A., Fabris, G., Velotto, S., Scala, M., & Kontogiannis, T. (2023). A framework for supporting adaptive human-AI teaming in air traffic control. In D. Harris & W.-C. Li (Eds.), *Lecture Notes in Computer Science, LNAI* (Vol. 14018, pp. 320–330). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-35389-5\\_22](https://doi.org/10.1007/978-3-031-35389-5_22)
- Maletzki, C., Elsenbast, C., & Reuter-Oppermann, M. (2024). Towards human-AI interaction in medical emergency call handling. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (pp. 3374–3383). IEEE Computer Society.
- Mallick, R., Flathmann, C., Lancaster, C., Hauptman, A., McNeese, N., & Freeman, G. (2024). The pursuit of happiness: The power and influence of AI teammate emotion in human-AI teamwork. *Behaviour & Information Technology*, 43(14), 3436–3460. <https://doi.org/10.1080/0144929X.2023.2277909>
- Marhraoui, M. A., Janati Idrissi, M. A., & El Manouar, A. (2022). An integrated human-AI framework towards organizational agility and sustainable performance. In M. B. Ahmed, A. A. Boudhir, I. R. Kara, V. Jain, & S. Mellouli (Eds.), *Lect. Notes Networks Syst.* (Vol. 393, pp. 73–87), Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-94191-8\\_7](https://doi.org/10.1007/978-3-030-94191-8_7)
- Marri, S. (2023). A conceptual framework for conversational human-AI interaction design (CHAI). In A. Chakrabarti & V. Singh (Eds.), *Smart Innov. Syst. Technol.* (Vol. 343, pp. 627–640). Springer Science and Business Media Deutschland GmbH.
- Matamoros, A. R., Marconi, L., Zoppis, I. F., Manzoni, S. L., Mauri, G., Musiu, E. (2021). *Enhancing teachers-AI collaboration: Human computer interaction techniques for recommender systems in educational platforms*. <https://hdl.handle.net/10281/390669>
- McNeese, N. J., Schelble, B. G., Canonico, L. B., & Demir, M. (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>
- Mehta, V., Kaza, K., Dadboud, F., Bolic, M., & Mantegh, I. (2023). Enhancing counter drone operations through human-AI collaboration: A hierarchical decision-making framework. In *AIAA IEEE Dig. Avionics Syst. Conf. Proceeding Institute of Electrical and Electronics Engineers Inc.* <https://doi.org/10.1109/DASC58513.2023.10311244>
- Meier, S. & Glinka, K. (2023). To classify is to interpret: Building taxonomies from heterogeneous data through human-AI collaboration. In *Proceedings of Mensch Und Computer 2023 (MuC '23)* (pp. 395–401). Association for Computing Machinery. <https://doi.org/10.1145/3603555.3608532>
- Memmert, L. & Bittner, E. (2022). Complex problem solving through human-AI collaboration: Literature review on research contexts. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (Vol. 2022, pp. 378–387). IEEE Computer Society.
- Memmert, L. & Bittner, E. (2024). Human-AI collaboration for brainstorming: Effect of the presence of AI ideas on breadth of exploration. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (pp. 421–430). IEEE Computer Society.
- Mentzas, G., Lepenioti, K., Bousdekis, A., & Apostolou, D. (2021). Data-driven collaborative human-AI decision making. In D. Dennehy, A. Griva, N. Pouloudi, Y. K. Dwivedi, Y. K. Dwivedi, I. Pappas, I. Pappas, & M. Mantymaki (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 12896, pp. 120–131). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-85447-8\\_11](https://doi.org/10.1007/978-3-030-85447-8_11)
- Mesbah, S., Arous, I., Yang, J., & Bozzon, A. (2023). HybridEval: A human-AI collaborative approach for evaluating design ideas at scale. In *Proceedings of the ACM Web Conference 2023 (WWW '23)* (pp. 3837–3848). Association for Computing Machinery. <https://doi.org/10.1145/3543507.3583496>
- Meske, C. & Bunde, E. (2020). Transparency and trust in human-AI interaction: The role of model-agnostic explanations in computer vision-based decision support. In H. Degen & L. Reinerman-Jones (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 12217, pp. 54–69). Springer. [https://doi.org/10.1007/978-3-030-50334-5\\_4](https://doi.org/10.1007/978-3-030-50334-5_4)
- Metcalfe, J. S., Perelman, B. S., Boothe, D. L., & McDowell, K. (2021). Systemic oversimplification limits the potential for human-AI partnership. *IEEE Access*, 9, 70242–70260. <https://doi.org/10.1109/ACCESS.2021.3078298>
- Meyer, K. & Voigt, B.-F. (2022). Process wins and losses in dynamic human-AI interplay—A socio-psychological research perspective on collaborative performance. In L. M. Camarinha-Matos, A. Ortiz, X. Boucher, & A. L. Osório (Eds.), *IFIP Advances in Information and Communication Technology* (Vol. 662, pp. 289–302). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-14844-6\\_23](https://doi.org/10.1007/978-3-031-14844-6_23)
- Meyer-Vitali, A. & Mulder, W. (2024). Human-AI engineering for adults. In F. Lorig, J. Tucker, A. D. Lindstrom, F. Dignum, P. Murukannaiah, A. Theodorou, & P. Yolum (Eds.), *Frontiers in artificial intelligence and applications* (Vol. 386, pp. 228–240). IOS Press BV. <https://doi.org/10.3233/FAIA240197>
- Micchi, G., Bigo, L., Giraud, M., Groult, R., & Levé, F. (2021). I keep counting: An experiment in human/AI co-creative songwriting. *Transactions of the International Society for Music Information Retrieval*, 4(1), 263–275. <https://doi.org/10.5334/tismir.93>
- Milella, F., Natali, C., Scantamburlo, T., Campagner, A., & Cabitza, F. (2023). The impact of gender and personality in human-AI teaming: The case of collaborative question answering. In J. Abdelnour Nocera, M. Kristín Lárusdóttir, H. Petrie, A. Piccinno, & M. Winckler (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 14143, pp. 329–349). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-42283-6\\_19](https://doi.org/10.1007/978-3-031-42283-6_19)
- Mlynář, J., Depeursinge, A., Prior, J. O., Schaer, R., Martroye de Joly, A., & Évéquoz, F. (2024). Making sense of radiomics: Insights on human-AI collaboration in medical interaction from an observational user study. *Frontiers in Communication*, 8, 1234987. <https://doi.org/10.3389/fcomm.2023.1234987>
- Mohanty, P., Grundstrom, C., Monteiro, E., & Zhang, Z. (2024). Tensions in the transition of human-AI collaboration: A case study of the nordic renewable energy sector. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (pp. 257–266). IEEE Computer Society.
- Molenaar, I. (2022a). The concept of hybrid human-AI regulation: Exemplifying how to support young learners' self-regulated learning.

- Computers and Education: Artificial Intelligence*, 3, 100070. <https://doi.org/10.1016/j.caeai.2022.100070>
- Molenaar, I. (2022b). Towards hybrid human-AI learning technologies. *European Journal of Education*, 57(4), 632–645. <https://doi.org/10.1111/ejed.12527>
- Morrison, R., Fidge, N. H., & Grego, B. (1990). Studies on the formation, separation, and characterization of cyanogen bromide fragments of human AI apolipoprotein. *Analytical Biochemistry*, 186(1), 145–152. [https://doi.org/10.1016/0003-2697\(90\)90588-Z](https://doi.org/10.1016/0003-2697(90)90588-Z)
- Morrison, K., Shin, D., Holstein, K., & Perer, A. (2023). Evaluating the impact of human explanation strategies on human-AI visual decision-making. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW1), 1–37. <https://doi.org/10.1145/3579481>
- Morrison, K., Spitzer, P., Turri, V., Feng, M., Kühl, N., & Perer, A. (2024). The impact of imperfect XAI on human-AI decision-making. *Proceedings of the ACM on Human-Computer Interaction*, 8(CSCW1), 1–39. <https://doi.org/10.1145/3641022>
- Moruzzi, C. & Margarido, S. (2024). A user-centered framework for human-AI co-creativity. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3650929>
- Mou, Y. & Xu, K. (2017). The media inequality: Comparing the initial human-human and human-AI social interactions. *Computers in Human Behavior*, 72, 432–440. <https://doi.org/10.1016/j.chb.2017.02.067>
- Mozannar, H., Lee, J. J., Wei, D., Sattigeri, P., Das, S., & Sontag, D. (2023). Effective human-AI teams via learned natural language rules and onboarding. In A. Oh, T. Neumann, A. Globerson, K. Saenko, M. Hardt, & S. Levine (Eds.), *Advances in neural information processing systems* (Vol. 36). Neural Information Processing Systems Foundation.
- Mucha, H., Robert, S., Breitschwerdt, R., & Fellmann, M. (2021). Interfaces for explanations in human-AI interaction: Proposing a design evaluation approach. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems (CHI EA '21)*. Association for Computing Machinery. <https://doi.org/10.1145/3411763.3451759>
- Muijlwijk, H., Willemsen, M. C., Smyth, B., & IJsselstein, W. A. (2024). Benefits of human-AI interaction for expert users interacting with prediction models: A study on marathon running. In *Proceedings of the 29th International Conference on Intelligent User Interfaces (IUI '24)* (pp. 245–258). Association for Computing Machinery. <https://doi.org/10.1145/3640543.3645205>
- Mulder, W. & Meyer-Vitali, A. (2023). A maturity model for collaborative agents in human-AI ecosystems. In L. M. Camarinha-Matos, X. Boucher, & A. Ortiz (Eds.), *IFIP Advances in Information and Communication Technology, AICT* (Vol. 688, pp. 328–335). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-42622-3\\_23](https://doi.org/10.1007/978-3-031-42622-3_23)
- Muller, M. & Weisz, J. (2022). Extending a human-AI collaboration framework with dynamism and sociality. In *Proceedings of the 1st Annual Meeting of the Symposium on Human-Computer Interaction for Work (CHIWORK '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3533406.3533407>
- Muller, M., Weisz, J. D., Houde, S., & Ross, S. I. (2024). Drinking chai with your (AI) programming partner: Value tensions in the tokenization of future human-AI collaborative work. In *Proceedings of the 3rd Annual Meeting of the Symposium on Human-Computer Interaction for Work (CHIWORK '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3663384.3663390>
- Munn, Z., Peters, M. D. J., Stern, C., Tufanaru, C., McArthur, A., & Aromataris, E. (2018). Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC Medical Research Methodology*, 18, 1–7. <https://doi.org/10.1186/s12874-018-0611-x>
- Munyaka, I., Ashktorab, Z., Dugan, C., Johnson, J., & Pan, Q. (2023). Decision making strategies and team efficacy in human-AI teams. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW1), 1–24. <https://doi.org/10.1145/3579476>
- Naikar, N., Brady, A., Moy, G., & Kwok, H.-W. (2023). Designing human-AI systems for complex settings: Ideas from distributed, joint, and self-organising perspectives of sociotechnical systems and cognitive work analysis. *Ergonomics*, 66(11), 1669–1694. <https://doi.org/10.1080/00140139.2023.2281898>
- Naser, M. Y. M. & Bhattacharya, S. (2023). Empowering human-AI teams via intentional behavioral synchrony. *Frontiers in Neuroergonomics*, 4, 1181827. <https://doi.org/10.3389/fnrgo.2023.1181827>
- Navidi, N. & Landry, R. Jr. (2021). New approach in human-AI interaction by reinforcement-imitation learning. *Applied Sciences (Switzerland)*, 11(7), 3068. <https://doi.org/10.3390/app11073068>
- Nazarenko, A. A. & Camarinha-Matos, L. M. (2024). A human-AI Framework to Design Collaborative Cyber Physical Systems. In L. M. Camarinha-Matos & F. Ferrada (Eds.), *IFIP Advances in Information and Communication Technology IFIPACT* (Vol. 716, pp. 28–42). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-63851-0\\_2](https://doi.org/10.1007/978-3-031-63851-0_2)
- Neumayr, T. & Augstein, M. (2020). A systematic review of personalized collaborative systems. *Frontiers in Computer Science*, 2. <https://doi.org/10.3389/fcomp.2020.562679>
- Neuwirth, R. J. & Migliorini, S. (2022). Unacceptable risks in human-AI collaboration: Legal prohibitions in light of cognition, trust and harm. In M. B. Ganapini, A. Loreggia, N. Mattei, F. Rossi, B. Srivastava, & B. Venable (Eds.), *CEUR Workshop Proceeding* (Vol. 3547). CEUR-WS.
- Nguyen, A., Hong, Y., Dang, B., & Huang, X. (2024). Human-AI collaboration patterns in AI-assisted academic writing. *Studies in Higher Education*, 49(5), 847–864. <https://doi.org/10.1080/03075079.2024.2323593>
- Nguyen, A. T., Kharosekar, A., Krishnan, S., Krishnan, S., Tate, E., Wallace, B. C., & Lease, M. (2018). Believe it or not: Designing a human-AI partnership for mixed-initiative fact-checking. In *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology (UIST '18)* (pp. 189–199). Association for Computing Machinery. <https://doi.org/10.1145/3242587.3242666>
- Nguyen, G., Taesiri, M. R., & Nguyen, A. (2022). Visual correspondence-based explanations improve AI robustness and human-AI team accuracy. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, & A. Oh (Eds.), *Advances in neural information processing systems* (Vol. 35). Neural Information Processing Systems Foundation.
- Niehaus, J. & Weyhrauch, P. (2011). Towards an architecture for collaborative human/AI control of interactive characters. In *Lecture Notes in Computer Science, LNAI* (Vol. 6525, pp. 67–75). Springer. [https://doi.org/10.1007/978-3-642-18181-8\\_5](https://doi.org/10.1007/978-3-642-18181-8_5)
- Nikookar, S. (2023). Human-AI complex task planning. In *Proceeding Int. Conf. Data Eng.* (Vol. 2023, pp. 3923–3927). IEEE Computer Society. <https://doi.org/10.1109/ICDE55515.2023.00382>
- Ning, Z., Zhang, Z., Ban, J., Jiang, K., Gan, R., Tian, Y., & Li, T. J.-J. (2024). MIMOSA: Human-AI co-creation of computational spatial audio effects on videos. In *Proceedings of the 16th Conference on Creativity & Cognition (C&C '24)* (pp. 156–169). Association for Computing Machinery. <https://doi.org/10.1145/3635636.3656189>
- Nols, T., Ulfert-Blank, A.-S., & Parush, A. (2023). Trust dispersion and effective human-AI collaboration: The role of psychological safety. In P. K. Murukannaiah & T. Hirzle (Eds.), *CEUR Workshop Proceeding* (Vol. 3456, pp. 157–163). CEUR-WS.
- Nunes, I. & Jannach, D. (2017). A systematic review and taxonomy of explanations in decision support and recommender systems. *User Modeling and User-Adapted Interaction*, 27(3–5), 393–444. <https://doi.org/10.1007/s11257-017-9195-0>
- Ogiela, U., Takizawa, M., & Ogiela, M. R. (2022). Human-AI protocols for cloud data management. In L. Barolli, H. Miwa, & T. Enokido (Eds.), *Lect. Notes Networks Syst., LNNS* (Vol. 526, pp. 115–118). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-14314-4\\_11](https://doi.org/10.1007/978-3-031-14314-4_11)
- Okamura, K. & Yamada, S. (2020a). Adaptive trust calibration for human-AI collaboration. *PLoS One*, 15(2), e0229132. <https://doi.org/10.1371/journal.pone.0229132>



- Okamura, K. & Yamada, S. (2020b). Empirical evaluations of framework for adaptive trust calibration in human-AI cooperation. *IEEE Access*, 8, 220335–220351. <https://doi.org/10.1109/ACCESS.2020.3042556>
- Oksana, M., Kotsipak, S., Dolgikh, Y., Bilak, T., Radivilova, & O., Baranovskyi. (2022). Collaborative human-AI Decision-Making Systems with Numerical Channels. In *Proceeding—Int. Conf. Adv. Comput. Inf. Technol.* (pp. 5–8). <https://doi.org/10.1109/ACIT54803.2022.9913201>
- Omidvar-Tehrani, B., Ishaani, M., & Anubhai, A. (2024). Evaluating human-AI partnership for LLM-based code migration. In *Conf. Hum. Fact Comput. Syst. Proceeding Association for Computing Machinery*. <https://doi.org/10.1145/3613905.3650896>
- Ong, C., McGee, K., & Chuah, T. L. (2012). Closing the human-AI team-mate gap: How changes to displayed information impact player behavior towards computer teammates. In *Proceedings of the 24th Australian Computer-Human Interaction Conference (OzCHI '12)* (pp. 433–439). Association for Computing Machinery. <https://doi.org/10.1145/2414536.2414604>
- O'Regan, G. & O'Regan. (2008). *A brief history of computing*. Springer.
- Orzikulova, A., Xiao, H., Li, Z., Yan, Y., Wang, Y., Shi, Y., Ghassemi, M., Lee, S.-J., Dey, A. K., & Xu, X. (2024). Time2Stop: Adaptive and explainable human-AI loop for smartphone overuse intervention. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642747>
- Ou, C., Buschek, D., Mayer, S., & Butz, A. (2022). The human in the infinite loop: A case study on revealing and explaining human-AI interaction loop failures. In *Proceedings of Mensch Und Computer 2022 (MuC '22)* (pp. 158–168). Association for Computing Machinery. <https://doi.org/10.1145/3543758.3543761>
- Overney, C., Saldías, B., Dimitrakopoulou, D., & Roy, D. (2024). SenseMate: An accessible and beginner-friendly human-AI platform for qualitative data analysis. In *Proceedings of the 29th International Conference on Intelligent User Interfaces (IUI '24)* (pp. 922–939). Association for Computing Machinery. <https://doi.org/10.1145/3640543.3645194>
- Padovano, A. & Cardamone, M. (2024). Towards human-AI collaboration in the competency-based curriculum development process: The case of industrial engineering and management education. *Computers and Education: Artificial Intelligence*, 7, 100256. <https://doi.org/10.1016/j.caeai.2024.100256>
- Paiva, R. & Bittencourt, I. I. (2020). Helping teachers help their students: A human-AI hybrid approach. In I. I. Bittencourt, M. Cukurova, R. Luckin, K. Muldner, & E. Millán (Eds.), *Lecture Notes in Computer Science, LNAI* (Vol. 12163, pp. 448–459). Springer. [https://doi.org/10.1007/978-3-030-52237-7\\_36](https://doi.org/10.1007/978-3-030-52237-7_36)
- Pan, W., Liu, D., Meng, J., & Liu, H. (2024). Human-AI communication in initial encounters: How AI agency affects trust, liking, and chat quality evaluation. *New Media & Society*. <https://doi.org/10.1177/14614448241259149>
- Pandya, R., Huang, S. H., Hadfield-Menell, D., & Dragan, A. D. (2019). Human-AI learning performance in multi-armed bandits. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (AI/ES '19)* (pp. 369–375). Association for Computing Machinery. <https://doi.org/10.1145/3306618.3314245>
- Papachristos, E., Johansen, P. S., Jacobsen, R. M., Bysted, L. B. L., & Skov, M. B. (2021). How do people perceive the role of AI in human-AI collaboration to solve everyday tasks?. In *CHI Greece 2021: 1st International Conference of the ACM Greek SIGCHI Chapter (CHI Greece 2021)*. Association for Computing Machinery. <https://doi.org/10.1145/3489410.3489420>
- Parekh, G., DeLatte, D., Herman, G. L., Oliva, L., Phatak, D., Scheponik, T., & Sharman, A. T. (2018). Identifying core concepts of cybersecurity: Results of two Delphi processes. *IEEE Transactions on Education*, 61(1), 11–20. <https://doi.org/10.1109/TE.2017.2715174>
- Park, H., Ahn, D., Hosanagar, K., & Lee, J. (2021). Human-AI interaction in human resource management: Understanding why employees resist algorithmic evaluation at workplaces and how to mitigate burdens. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery. <https://doi.org/10.1145/3411764.3445304>
- Pataranutaporn, P., Mano, P., Bhongse-Tong, P., Chongchadklang, T., Archiwaranguprok, C., Hantrakul, L., Eaimsa-Ard, J., Maes, P., & Klunchun, P. (2024). Human-AI co-dancing: Evolving cultural heritage through collaborative choreography with generative virtual characters. In *Proceedings of the 9th International Conference on Movement and Computing (MOCO '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3658852.3661317>
- Pawlick-Potts, D. (2022). Is anybody in there? Towards a model of affect and trust in human-AI information interactions. *Information Research: An International Electronic Journal*, 27(Special Issue), isic2230. <https://doi.org/10.47989/irisic2230>
- Peeters, M. M. M., van Diggelen, J., van den Bosch, K., Bronkhorst, A., Neerincx, M. A., Schraagen, J. M., & Raaijmakers, S. (2021). Hybrid collective intelligence in a human-AI society. *AI & Society*, 36(1), 217–238. <https://doi.org/10.1007/s00146-020-01005-y>
- Peng, B., Nushi, E., Kiciman, K., Inkpen, & E., Kamar. (2022). Investigations of performance and bias in human-AI teamwork in hiring. In *Proceeding AAAI Conf. Artif. Intell.*, AAAI (Vol. 36, pp. 12089–12097). Association for the Advancement of Artificial Intelligence.
- Pereira, F. D., Rodrigues, L., Henklain, M. H. O., Freitas, H., Oliveira, D. F., Cristea, A. I., Carvalho, L., Isotani, S., Benedict, A., Dorodchi, M., & De Oliveira, E. H. T. (2023). Toward human-AI collaboration: A recommender system to support CS1 instructors to select problems for assignments and exams. *IEEE Transactions on Learning Technologies*, 16(3), 457–472. <https://doi.org/10.1109/TLT.2022.3224121>
- Pereira, F. D., Pires, F., Fonseca, S. C., Oliveira, E. H. T., Carvalho, L. S. G., Oliveira, D. B. F., & Cristea, A. I. (2021). Towards a human-AI hybrid system for categorising programming problems. In *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education (SIGCSE '21)* (pp. 94–100). Association for Computing Machinery. <https://doi.org/10.1145/3408877.3432422>
- Peters, M. D. J., Godfrey, C. M., Khalil, H., McInerney, P., Parker, D., & Soares, C. B. (2015). Guidance for conducting scoping reviews. *International Journal of Evidence-Based Healthcare*, 13(3), 141–146. <https://doi.org/10.1097/XEB.0000000000000050>
- Petrescu, M. & Krishen, A. S. (2023). Hybrid intelligence: Human-AI collaboration in marketing analytics. *Journal of Marketing Analytics*, 11(3), 263–274. <https://doi.org/10.1057/s41270-023-00245-3>
- Pham, D., Menon, V., Tenhundfeld, N., Weger, K., Mesmer, B., Gholston, S., & Davis, T. (2022). A case study of human-AI interactions using transparent AI-driven autonomous systems for improved human-AI trust factors. In D. Kaber, A. Guerrieri, G. Fortino, & A. Nurnberger (Eds.), *Proceeding IEEE Int. Conf. Hum.-Mach. Syst., ICHMS*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICHMS56717.2022.9980662>
- Prabhudesai, S., Yang, L., Asthana, S., Huan, X., Liao, Q. V., & Banovic, N. (2023). Understanding uncertainty: How lay decision-makers perceive and interpret uncertainty in human-AI decision making. In *Proceedings of the 28th International Conference on Intelligent User Interfaces (IUI '23)* (pp. 379–396). Association for Computing Machinery. <https://doi.org/10.1145/3581641.3584033>
- Prajwal, M., Raj, A., Sen, S., Saha, S., & Ghosh, S. (2023). Towards efficient emotion self-report collection using human-AI collaboration: A case study on smartphone keyboard interaction. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 7(2), 1–23. <https://doi.org/10.1145/3596269>
- Puerta-Beldarrain, M., Gómez-Carmona, O., Casado-Mansilla, D., & López-de Ipiña, D. (2023). Human-AI collaboration to promote trust, engagement and adaptation in the process of pro-environmental and health behaviour change. In J. Bravo, S. Ochoa, & J. Favela (Eds.), *Lect. Notes Networks Syst., LNNS* (Vol. 594, pp. 381–392). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-21333-5\\_38](https://doi.org/10.1007/978-3-031-21333-5_38)
- Puig, X., Shu, T., Li, S., Wang, Z., Liao, Y.-H., Tenenbaum, J. B., Fidler, S., & Torralba, A. (2021). Watch-and-help: A challenge for social perception and human-AI collaboration. In *ICLR—Int. Conf. Learn. Represent.*. International Conference on Learning Representations, ICLR.

- Puranam, P. (2021). Human-AI collaborative decision-making as an organization design problem. *Journal of Organization Design*, 10(2), 75–80. <https://doi.org/10.1007/s41469-021-00095-2>
- Qadir, J., Islam, M. Q., & Al-Fuqaha, A. (2022). Toward accountable human-centered AI: Rationale and promising directions. *Journal of Information, Communication and Ethics in Society*, 20(2), 329–342. <https://doi.org/10.1108/JICES-06-2021-0059>
- Qian, C., & Wexler, J. (2024). Take it, leave it, or fix it: Measuring productivity and trust in human-AI collaboration. In *Proceedings of the 29th International Conference on Intelligent User Interfaces (IUI '24)* (pp. 370–384). Association for Computing Machinery. <https://doi.org/10.1145/3640543.3645198>
- Raees, M., Meijerink, I., Lykourantzou, I., Khan, V.-J., & Papangelis, K. (2024). From explainable to interactive AI: A literature review on current trends in human-AI interaction. *International Journal of Human-Computer Studies*, 189, 103301. <https://doi.org/10.1016/j.ijhcs.2024.103301>
- Rago, F. (2022). A new matrix model for human-AI integration. In K. Arai (Ed.), *Lect. Notes Networks Syst., LNNS* (Vol. 358, pp. 114–120). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-89906-6\\_9](https://doi.org/10.1007/978-3-030-89906-6_9)
- Rajagopal, A. & Vedamanickam, N. (2019). New approach to human AI interaction to address digital divide AI divide: Creating an interactive AI platform to connect teachers students. In *Proceeding IEEE Int. Conf. Electr., Comput. Commun. Technol., ICECCT*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICECCT.2019.8869174>
- Ramchurn, S. D., Stein, S., & Jennings, N. R. (2021). Trustworthy human-AI partnerships. *iScience*, 24(8), 102891. <https://doi.org/10.1016/j.isci.2021.102891>
- Rana, M. & Bansal, J. (2023). The future of OpenAI tools: Opportunities and challenges for human-AI collaboration. In *Int. Conf. Futur. Technol., INCOFT*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/INCOFT60753.2023.10424990>
- Rastogi, C., Ribeiro, M. T., King, N., Nori, H., & Amershi, S. (2023). Supporting human-AI collaboration in auditing LLMs with LLMs. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society (AIES '23)* (pp. 913–926). Association for Computing Machinery. <https://doi.org/10.1145/3600211.3604712>
- Rathje, S., Mirea, D.-M., Sucholutsky, I., Marjeh, R., Robertson, C. E., & Bavel, J. J. V. (2024). GPT is an effective tool for multilingual psychological text analysis. *Proceedings of the National Academy of Sciences of the United States of America*, 121. <https://api.semanticscholar.org/CorpusID:271857253>
- Ray, Y., Yao, R., Kumar, A., Divakaran., & G., Burachas. (2019). Can you explain that? Lucid explanations help human-AI collaborative image retrieval. In E. Law & J. W. Vaughan (Eds.), *Proceeding AAAI. Conference on Human Computer Crowdsourcing* (Vol. 7, pp. 153–161). Association for the Advancement of Artificial Intelligence. <https://doi.org/10.1609/hcomp.v7i1.5275>
- Razmerita, L., Brun, A., & Nabeth, T. (2022). Collaboration in the machine age: Trustworthy human-AI collaboration. In *Learn. Anal. Intell. Syst.* (Vol. 24, pp. 333–356). Springer Nature. [https://doi.org/10.1007/978-3-030-93052-3\\_14](https://doi.org/10.1007/978-3-030-93052-3_14)
- Reverberi, C., Rigon, T., Solari, A., Hassan, C., Cherubini, P., Cherubini, A., Awadie, H., Bernhofer, S., Carballal, S., Dinis-Ribeiro, M., Fernández-Clotett, A., Esparrach, G. F., Gralnek, I., Higasa, Y., Hirabayashi, T., Hirai, T., Iwatate, M., Kawano, M., Mader, M., ... Tanaka, Y, GI Genius CADx Study Group (2022). Experimental evidence of effective human-AI collaboration in medical decision-making. *Scientific Reports*, 12(1), 14952. <https://doi.org/10.1038/s41598-022-18751-2>
- Rezwana, J., & Maher, M. L. (2021). COFI: A framework for modeling interaction in human-AI co-creative systems. In A. G. de Silva Garza, T. Veale, W. Aguilar, & R. Perez y Perez (Eds.), *Proceeding Int. Conf. Comput. Creat., ICC3* (pp. 444–448). Association for Computational Creativity (ACC).
- Rezwana, J., Maher, M. L., & Davis, N. (2021). Creative PenPal: A virtual embodied conversational AI agent to improve user engagement and collaborative experience in human-AI co-creative design ideation. In D. Glowacka & V. Krishnamurthy (Eds.), *CEUR Workshop Proceeding* (Vol. 2903). CEUR-WS.
- Rezwana, J. & Maher, M. L. (2022). Understanding user perceptions, collaborative experience and user engagement in different human-AI interaction designs for co-creative systems. In *Proceedings of the 14th Conference on Creativity and Cognition (C&C '22)* (pp. 38–48). Association for Computing Machinery. <https://doi.org/10.1145/3527927.3532789>
- Rezwana, J. & Maher, M. L. (2023a). User perspectives of the ethical dilemmas of ownership, accountability, leadership in human-AI co-creation. In A. Smith-Renner & P. Taele (Eds.), *CEUR Workshop Proceeding* (Vol. 3359, pp. 81–88). CEUR-WS.
- Rezwana, J. & Maher, M. L. (2023b). Designing creative AI partners with COFI: A framework for modeling interaction in human-AI co-creative systems. *ACM Transactions on Computer-Human Interaction*, 30(5), 1–28. <https://doi.org/10.1145/3519026>
- Rezwana, J. & Maher, M. L. (2023c). User perspectives on ethical challenges in human-AI co-creativity: A design fiction study. In *Proceedings of the 15th Conference on Creativity and Cognition (C&C '23)* (pp. 62–74). Association for Computing Machinery. <https://doi.org/10.1145/3591196.3593364>
- Richburg, C., Bao, & M., Carpuat. (2024). Automatic authorship analysis in human-AI collaborative writing. In N. Calzolari, M.-Y. Kan, V. Hoste, A. Lenci, S. Sakti, & N. Xue (Eds.), *Jt. Int. Conf. Comput. Linguist., Lang. Resour. Eval., LREC-COLING—Main Conf. Proceeding* (pp. 1845–1855), European Language Resources Association (ELRA).
- Rinott, M. & Shaer, O. (2024). Temporal aspects of human-AI collaborations for work. In *Proceedings of the 3rd Annual Meeting of the Symposium on Human-Computer Interaction for Work (CHIWORK '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3663384.3663397>
- Robertson, J., Ferreira, C., Botha, E., & Oosthuizen, K. (2024). Game changers: A generative AI prompt protocol to enhance human-AI knowledge co-construction. *Business Horizons*, 67(5), 499–510. <https://doi.org/10.1016/j.bushor.2024.04.008>
- Roeder, L., Hoyte, P., van der Meer, J., Fell, L., Johnston, P., Kerr, G., & Bruza, P. (2023). A quantum model of trust calibration in human-AI interactions. *Entropy*, 25(9), 1362. <https://doi.org/10.3390/e25091362>
- Ruissalo, J. (2024). Transition to human-AI work: Shifts in routines' dynamics and the implications for roles in knowledge-intensive work. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (pp. 5806–5815). IEEE Computer Society.
- Sachan, S., Almaghrabi, F., Yang, J.-B., & Xu, D.-L. (2024). Human-AI collaboration to mitigate decision noise in financial underwriting: A study on FinTech innovation in a lending firm. *International Review of Financial Analysis*, 93, 103149. <https://doi.org/10.1016/j.irfa.2024.103149>
- Sackman, H. (1974). *Delphi Assessment: Expert Opinion, Forecasting, and Group Process*. Technical Report. United States Air Force Project Rand. <https://www.rand.org/pubs/reports/R1283.html>
- Sadeghian, S., Uhde, A., & Hassenzahl, M. (2024). The soul of work: Evaluation of job meaningfulness and accountability in human-AI collaboration. *Proceedings of the ACM on Human-Computer Interaction*, 8(CSCW1), 1–26. <https://doi.org/10.1145/3637407>
- Saffiotti, P., Fogel, P., Knudsen, L., de Miranda, & O., Thörn. (2020). On human-AI collaboration in artistic performance. In A. Saffiotti, L. Serafini, & P. Lukowicz (Eds.), *CEUR Workshop Proceeding* (Vol. 2659, pp. 38–43). CEUR-WS.
- Salah, M., Abdelfattah, F., Halbusi, H. A., & Mohammed, M. (2023). Beyond the “death of research”: Reimagining the human-AI collaboration in scientific research. *Changing Societies & Personalities*, 7(4), 31–46. <https://doi.org/10.15826/csp.2023.7.4.250>
- Salehi, E. K., Chiou, M., Mancenido, A., Mosallanezhad, M. C., Cohen, & A., Shah. (2021). Decision deferral in a human-AI joint face-matching task: Effects on human performance and trust. In *Proc Hum Factors Ergon Soc.* (Vol. 65, No. 1, pp. 638–642). SAGE Publications Inc. <https://doi.org/10.1177/1071181321651157>
- Salikutluk, V., Frodl, E., Herbert, F., Balfanz, D., & Koert, D. (2023). Situational adaptive autonomy in human-AI cooperation. In P. Frohlich, M. Baldauf, P. Palanque, V. Roto, F. Paterno, W. Ju, M.



- Tscheligi, & M. Tscheligi (Eds.), *CEUR Workshop Proceeding* (Vol. 3394). CEUR-WS.
- Salikutluk, V., Schöpper, J., Herbert, F., Scheuermann, K., Frodl, E., Balfanz, D., Jäkel, F., & Koert, D. (2024). An evaluation of situational autonomy for human-AI collaboration in a shared workspace setting. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642564>
- Salimzadeh, S., He, G., & Gadiraju, U. (2023). A missing piece in the puzzle: Considering the role of task complexity in human-AI decision making. In *Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization (UMAP '23)* (pp. 215–227). Association for Computing Machinery. <https://doi.org/10.1145/3565472.3592959>
- Salimzadeh, S., He, G., & Gadiraju, U. (2024). Dealing with uncertainty: Understanding the impact of prognostic versus diagnostic tasks on trust and reliance in human-AI decision-making. In *Conf Hum Fact Comput Syst Proceeding* Association for Computing Machinery.
- Samadi, V., Stephens, K. K., Hughes, A., & Murray-Tuite, P. (2024). Challenges and opportunities when bringing machines onto the team: Human-AI teaming and flood evacuation decisions. *Environmental Modelling & Software*, 175, 105976. <https://doi.org/10.1016/j.envsoft.2024.105976>
- Sankaran, G., Palomino, M. A., Knahl, M., & Siestrup, G. (2022). A modeling approach for measuring the performance of a human-AI collaborative process. *Applied Sciences (Switzerland)*, 12(22), 11642. <https://doi.org/10.3390/app122211642>
- Sarkar, A. (2023). Enough with “human-AI collaboration. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544549.3582735>
- Sarkar, B., Shih, A., & Sadigh, D. (2023). Diverse conventions for human-AI collaboration. In A. Oh, T. Neumann, A. Globerson, K. Saenko, M. Hardt, & S. Levine (Eds.), *Advances in neural information processing systems* (Vol. 36), Neural Information Processing Systems Foundation.
- Sato, M., Terada, K., & Gratch, J. (2023). Preference learning from emotional expressions contributes integrative solutions between human-AI negotiation. In *Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos, ACIIW*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ACIIW59127.2023.10388197>
- Schapiro, M. M., Williams, M., Balch, A., Baron, R. J., Barrett, P., Beveridge, R., Collins, T., Day, S. C., Fernandopulle, R., Gilberg, A. M., Henley, D. E., Nguyen Howell, A., Laine, C., Miller, C., Ryu, J., Schwarz, D. F., Schwartz, M. D., Stevens, J., Teisberg, E., ... Hubbard, R. A. (2020). Seeking consensus on the terminology of value-based transformation through use of a Delphi process. *Population Health Management*, 23(3), 243–255. <https://doi.org/10.1089/pop.2019.0093>
- Schecter, A., Hohenstein, J., Larson, L., Harris, A., Hou, T.-Y., Lee, W.-Y., Lauharatanahirun, N., DeChurch, L., Contractor, N., & Jung, M. (2023). Vero: An accessible method for studying human-AI teamwork. *Computers in Human Behavior*, 141, 107606. <https://doi.org/10.1016/j.chb.2022.107606>
- Schelle, B. G., Flathmann, C., McNeese, N., & Canonico, L. B. (2021). Understanding human-AI cooperation through game-theory and reinforcement learning models. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (Vol. 2020, pp. 348–357). IEEE Computer Society.
- Schelle, B. G., Lancaster, C., Duan, W., Mallick, R., McNeese, N. J., & Lopez, J. (2023). The effect of AI teammate ethicality on trust outcomes and individual performance in human-AI teams. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (Vol. 2023, pp. 322–331). IEEE Computer Society.
- Schelle, B., Lopez, J., McNeese, N. J., Pak, R., Textor, C., Zhang, R., & Freeman, G. (2024). Towards ethical AI: Empirically investigating dimensions of AI ethics, trust repair, and performance in human-AI teaming. *Human Factors*, 66(4), 1037–1055. <https://doi.org/10.1177/00187208221116952>
- Schemmer, M., Bartos, A., Spitzer, P., Hemmer, P., Liebschner, J., Satzger, G., & Kühl, N. (2023). Towards effective human-AI decision-making: The role of human learning in appropriate reliance on AI Advice. In *International Conference on Information Systems, ICIS: “Rising like Phoenix: Emerg. Pandemic Reshaping Hum. Endeavors Digit. Technol.* Association for Information Systems.
- Schemmer, M., Hemmer, P., Nitsche, M., Kühl, N., & Vössing, M. (2022). A meta-analysis of the utility of explainable artificial intelligence in human-AI decision-making. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society (AIES '22)* (pp. 617–626). Association for Computing Machinery. <https://doi.org/10.1145/3514094.3534128>
- Schmidt, K. & Bannon, L. (1992). Taking CSCW seriously. *Computer Supported Cooperative Work (CSCW)*, 1(1–2), 7–40. <https://doi.org/10.1007/BF00752449>
- Schmidt, P., & Biessmann, F. (2020). Calibrating human-AI collaboration: Impact of risk, ambiguity and transparency on algorithmic bias. In *Lecture Notes in Computer Science*, Holzinger A., Holzinger A., Kieseberg P., Tjoa A.M., Weippl E., and Weippl E. (Eds.), Vol. 12279 LNCS. Springer. 431–449. [https://doi.org/10.1007/978-3-030-57321-8\\_24](https://doi.org/10.1007/978-3-030-57321-8_24)
- Schmitt, V., Villa-Arenas, L.-F., Feldhus, N., Meyer, J., Spang, R. P., & Möller, S. (2024). The role of explainability in collaborative human-AI disinformation detection. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency (FAcT '24)* (pp. 2157–2174). Association for Computing Machinery. <https://doi.org/10.1145/3630106.3659031>
- Schoeffer, J., De-Arteaga, M., & Kühl, N. (2024). explanations, fairness, and appropriate reliance in human-AI decision-making. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642621>
- Schoenherr, J. R., & Thomson, R. (2024). When AI fails, who do we blame? Attributing responsibility in human-AI interactions. *IEEE Transactions on Technology and Society*, 5(1), 61–70. <https://doi.org/10.1109/TTS.2024.3370095>
- Schoonderwoerd, T. A. J., Zoelen, E. M. V., Bosch, K. V. D., & Neerinx, M. A. (2022). Design patterns for human-AI co-learning: A wizard-of-Oz evaluation in an urban-search-and-rescue task. *International Journal of Human-Computer Studies*, 164, 102831. <https://doi.org/10.1016/j.ijhcs.2022.102831>
- Schroder, I., Constantiou, V. K., Tuunainen, & R. D., Austin. (2022). Human-AI Collaboration—Coordinating automation and augmentation tasks in a digital service company. In T. X. Bui (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (Vol. 2022, pp. 206–215). IEEE Computer Society.
- Schwalb, J., Menon, V., Tenhundfeld, N., Weger, K., Mesmer, B., & Gholston, S. (2022). A study of drone-based AI for enhanced human-AI trust and informed decision making in human-AI interactive virtual environments. In Kaber D., Guerrieri A., Fortino G., and Nurnberger A. (Eds.) *Proceeding IEEE Int. Conf. Hum.-Mach. Syst., ICHMS* Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICHMS56717.2022.9980625>
- Scotte, A. J. & De Silva, V. (2023). Towards a neuro-symbolic framework for multimodal human-AI interaction. In De Marsico M., Sanniti di Baja G., and Fred A.L.N. (Eds.), *Int. Conf. Pattern. Recognit. Appl. Method* (Vol. 1, pp. 932–939). Science and Technology Publications, Lda. <https://doi.org/10.5220/0011776300003411>
- Segal, A., Gal, K., Kamar, E., Horvitz, E., Lintott, C., & Walmsley, M. (2022). A new workflow for human-AI collaboration in citizen science (pp. 89–95). In *ACM Int. Conf. Proceeding Ser.* Association for Computing Machinery. <https://doi.org/10.1145/3524458.3547243>
- Serbanescu. (2024). Human-AI system co-creativity to build interactive digital narratives. In *Springer. Ser. Des. Innov.* (Vol. 37, pp. 388–398). Springer Nature. [https://doi.org/10.1007/978-3-031-49811-4\\_37](https://doi.org/10.1007/978-3-031-49811-4_37)
- Sergeyuk, A., Titov, S., & Izadi, M. (2024). In-IDE human-AI experience in the era of large language models; A literature review. In *Proceedings of the 1st ACM/IEEE Workshop on Integrated Development Environments (IDE '24)* (pp. 95–100). Association for Computing Machinery. <https://doi.org/10.1145/3643796.3648463>

- Seveso, A., Mercorio, F., & Mezzananza, M. (2021). A human-AI teaming approach for incremental taxonomy learning from text. In Zhou Z.-H. (Ed.), *IJCAI Int. Joint Conf. Artif. Intell.* (pp. 4917–4918). International Joint Conferences on Artificial Intelligence.
- Shah, C. (2010). Collaborative information seeking: A literature review. *Advances in Librarianship*, 32, 3–33. [https://doi.org/10.1108/S0065-2830\(2010\)0000032004](https://doi.org/10.1108/S0065-2830(2010)0000032004)
- Sharma, A., Lin, I. W., Miner, A. S., Atkins, D. C., & Althoff, T. (2023). Human-AI collaboration enables more empathic conversations in text-based peer-to-peer mental health support. *Nature Machine Intelligence*, 5(1), 46–57. <https://doi.org/10.1038/s42256-022-00593-2>
- Sharma, S., Rao, C., Brockett, A., Malhotra, N., Jojic, & B., Dolan. (2024). Investigating agency of LLMs in human-AI collaboration tasks. In Graham Y., Purver M., and Purver M. (Eds.), *EACL—Conf. European Chapter Assoc. Comput. Linguist., Proceeding Conf.* (Vol. 1, pp. 1968–1987). Association for Computational Linguistics (ACL).
- Shen, H., Liao, K., Liao, Z., Doornberg, J., Qiao, M., van den Hengel, A., & Verjans, J. W. (2021). Human-AI interactive and continuous sensemaking: A case study of image classification using scribble attention maps. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems (CHI EA '21)*. Association for Computing Machinery. <https://doi.org/10.1145/3411763.3451798>
- Shenoi, V. V., Sreeram, P., Sai Varma, C. L., Goud, K. R., & Afroz, S. N. (2024). Analysing the role of human-AI collaboration in workforce transformation. In *Int. Conf. Adv. Data Eng. Intell. Comput. Syst., ADICS*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ADICS58448.2024.10533640>
- Shergadwala, M. N. & El-Nasr, M. S. (2021). Human-centric design requirements and challenges for enabling human-AI interaction in engineering design: An interview study. In *Proceeding ASME Des. Eng. Tech. Conf.* (Vol. 6). American Society of Mechanical Engineers (ASME). <https://doi.org/10.1115/DETC2021-69809>
- Shi, C., Hu, Y., Wang, S., Ma, S., Zheng, C., Ma, X., & Luo, Q. (2023). RetroLens: A human-AI collaborative system for multi-step retrosynthetic route planning. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3581469>
- Shih, A., Sawhney, J., Kondic, S., Ermon, & D., Sadigh. (2021). On the critical role of conventions in adaptive human-AI collaboration. In *ICLR—Int. Conf. Learn. Represent.* International Conference on Learning Representations, ICLR.
- Shin, J., Hedderich, M. A., Rey, B. J., Lucero, A., & Oulasvirta, A. (2024). Understanding human-AI workflows for generating personas. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference (DIS '24)* (pp. 757–781). Association for Computing Machinery. <https://doi.org/10.1145/3643834.3660729>
- Shin, J. G., Kim, J. B., & Kim, S. H. (2019). A framework to identify critical design parameters for enhancing user's satisfaction in human-AI interactions. In *J. Phys. Conf. Ser.* (Vol. 1284, No. 1). Institute of Physics Publishing. <https://doi.org/10.1088/1742-6596/1284/1/012036>
- Shin, J.-G., Choi, G.-Y., Hwang, H.-J., & Kim, S.-H. (2021). Evaluation of emotional satisfaction using questionnaires in voice-based human-AI interaction. *Applied Sciences (Switzerland)*, 11(4), 1920. <https://doi.org/10.3390/app11041920>
- Shneiderman, B. (2021). Human-centered AI. *Issues in Science and Technology*, 37(2), 56–61. <https://www.jstor.org/stable/27092030>
- Shneiderman, B. (2022). *Human-centered AI*. Oxford University Press.
- Shukla, A., Shivakumar, M., Vasoya, Y., Pei, & A. F., Lyon. (2019). iLEAP: A human-AI teaming based mobile language learning solution for dual language learners in early and special educations. In Sanchez I.A., Isaías P., Ravesteijn P., Ongena G., and Rodrigues L. (Eds.) *Proceeding Int. Conf. Mob. Learn., ML* (pp. 57–64). IADIS Press. [https://doi.org/10.33965/ml2019\\_2019031008](https://doi.org/10.33965/ml2019_2019031008)
- Siemon, D. (2022). Elaborating team roles for artificial intelligence-based teammates in human-AI collaboration. *Group Decision and Negotiation*, 31(5), 871–912. <https://doi.org/10.1007/s10726-022-09792-z>
- Siirtola, P., & Rönning, J. (2019). Incremental learning to personalize human activity recognition models: The importance of human AI collaboration. *Sensors (Basel, Switzerland)*, 19(23), 5151. <https://doi.org/10.3390/s19235151>
- Simón, C., Revilla, E., & Jesús Sáenz, M. (2024). Integrating AI in organizations for value creation through Human-AI teaming: A dynamic-capabilities approach. *Journal of Business Research*, 182, 114783. <https://doi.org/10.1016/j.jbusres.2024.114783>
- Singh, S., Jain, S., & Jha, S. S. (2023). On subset selection of multiple humans to improve human-AI team accuracy. In *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems (AAMAS '23)* (pp. 317–325). International Foundation for Autonomous Agents and Multiagent Systems.
- Siu, H. C., Peña, J. D., Zhou, Y., Chen, E., Lopez, V. J., Palko, K., Chang, K. C., & Allen, R. E. (2021). Evaluation of human-AI teams for learned and rule-based agents in Hanabi. In Ranzato M., Beygelzimer A., Dauphin Y., Liang P.S., and Wortman Vaughan J. (Eds.), *Advances in neural information processing systems* (Vol. 20, PP. 16183–16195). Neural Information Processing Systems Foundation.
- Smirnov, A., Levashova, T., & Shilov, N. (2023). Human-AI collaboration types and standard tasks for decision support: Production system configuration use case. In Filipe J., Smialek M., Brodsky A., and Hammoudi S. (Eds.), *International Conference on Enterprise Information Systems, ICEIS—Proceedings* (Vol. 1, pp. 599–606). Science and Technology Publications, Lda. <https://doi.org/10.5220/0011987400003467>
- Smirnov, R., Ponomarev, A., & Levashova, T. (2023). Towards a methodology for developing human-AI collaborative decision support systems. In da Silva H.P., da Silva H.P., and Cipresso P. (Eds.), *Communications in computer and information science, CCIS* (Vol. 1996, pp. 69–88). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-49425-3\\_5](https://doi.org/10.1007/978-3-031-49425-3_5)
- Snatos, A., Brandão, B., Veloso, & J. B., de Vasconcelos. (2024). negative impacts of human-AI interaction in brands: A data mining exploratory approach. In Reis J.L., Santos J.P.M.D., Zelený J., and Gavurová B. (Eds.), *Smart Innov. Syst. Technol.* (Vol. 386, pp. 121–136). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-981-97-1552-7\\_9](https://doi.org/10.1007/978-981-97-1552-7_9)
- Song, B., Zhu, Q., & Luo, J. (2024). Human-AI collaboration by design. In Storga M., Skec S., Martinec T., Marjanovic D., Pavkovic N., and Skec M.M. (Eds.), *Proceeding Des. Soc.* (Vol. 4, pp. 2247–2256). Cambridge University Press. <https://doi.org/10.1017/pds.2024.227>
- Sowa, K., Przegalinska, A., & Ciechanowski, L. (2021). Cobots in knowledge work: Human – AI collaboration in managerial professions. *Journal of Business Research*, 125, 135–142. <https://doi.org/10.1016/j.jbusres.2020.11.038>
- Spina, D., Sanderson, M., Angus, D., Demartini, G., McKay, D., Saling, L. L., & White, R. W. (2023). Human-AI cooperation to tackle misinformation and polarization. *Communications of the ACM*, 66(7), 40–45. <https://doi.org/10.1145/3588431>
- Sqalli, M. T., Al-Thani, D., Qaraqe, M., & Fernandez-Luque, L. (2021). Perspectives on human-AI interaction applied to health and wellness management: Between milestones and Hurdles. In *Lect. Notes Bioeng.* (pp. 41–51). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-67303-1\\_4](https://doi.org/10.1007/978-3-030-67303-1_4)
- Sreedharan, S. (2023). Human-aware AI – A foundational framework for human-AI interaction. *AI Magazine*, 44(4), 460–466. <https://doi.org/10.1002/aaai.12142>
- Sreedharan, S., Kulkarni, A., Smith, D. E., & Kambhampati, S. (2021). A unifying Bayesian formulation of measures of interpretability in human-AI interaction. In Zhou Z.-H. (Ed.), *IJCAI Int. Joint Conf. Artif. Intell.* (pp. 4602–4610). International Joint Conferences on Artificial Intelligence.
- Stefanidi, E., Bentvelzen, M., Woźniak, P. W., Kosch, T., Woźniak, M. P., Mildner, T., Schneegass, S., Müller, H., & Niess, J. (2023). Literature reviews in HCI: A review of reviews. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1–24). ACM. <https://doi.org/10.1145/3544548.3581332>
- Stephens, K. K., Harris, A. G., Hughes, A., Montagnolo, C. E., Nader, K., Stevens, S. A., Tasuji, T., Xu, Y., Purohit, H., & Zobel, C. W. (2023). Human-AI teaming during an ongoing disaster: How scripts around training and feedback reveal this is a form of human-



- machine communication. *Human-Machine Communication*, 6, 65–85. <https://doi.org/10.30658/hmc.6.5>
- Stephens, K. K., Nader, K., Harris, A. G., Montagnolo, C. E., Hughes, A. L., Jarvis, S. A., Senarath, Y., & Purohit, H. (2021). Online-computer-mediated interviews and observations: Overcoming challenges and establishing best practices in a human-AI teaming context. In Bui T. X. (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (Vol. 2020, pp. 2896–2905). IEEE Computer Society.
- Stepin, I., Alonso, J. M., Catala, A., & Pereira-Fariña, M. (2021). A survey of contrastive and counterfactual explanation generation methods for explainable artificial intelligence. *IEEE Access*, 9, 11974–12001. <https://doi.org/10.1109/ACCESS.2021.3051315>
- Steyvers, M., Tejeda, H., Kerrigan, G., & Smyth, P. (2022). Bayesian modeling of human-AI complementarity. *Proceedings of the National Academy of Sciences of the United States of America*, 119(11), e2111547119. <https://doi.org/10.1073/PNAS.2111547119>
- Strobel, H., Kinley, J., Krueger, R., Beyer, J., Pfister, H., & Rush, A. M. (2022). Genni: Human-AI collaboration for data-backed text generation. *IEEE Transactions on Visualization and Computer Graphics*, 28(1), 1106–1116. <https://doi.org/10.1109/TVCG.2021.3114845>
- Su, Z., He, L., Jariwala, S. P., Zheng, K., & Chen, Y. (2022). “What is your envisioned future?”: Toward human-AI enrichment in data work of asthma care. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW2), 1–28. <https://doi.org/10.1145/3555157>
- Subramanian, H. V., Canfield, C., & Shank, D. B. (2024). Designing explainable AI to improve human-AI team performance: A medical stakeholder-driven scoping review. *Artificial Intelligence in Medicine*, 149, 102780. <https://doi.org/10.1016/j.artmed.2024.102780>
- Subramonyam, H., Im, J., Seifert, C., & Adar, E. (2022). Solving separation-of-concerns problems in collaborative design of human-AI systems through leaky abstractions. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3517537>
- Suh, S., Chen, M., Min, B., Li, T. J.-J., & Xia, H. (2024). Luminate: Structured generation and exploration of design space with large language models for human-AI co-creation. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642400>
- Sun, J., Yang, J., Zhou, G., Jin, Y., & Gong, J. (2024). Understanding human-AI collaboration in music therapy through co-design with therapists. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642764>
- Sundar, S. S. (2020). Rise of machine agency: A framework for studying the psychology of human-AI interaction (HAI). *Journal of Computer-Mediated Communication*, 25(1), 74–88. <https://doi.org/10.1093/jcmc/zmz026>
- Sutherland, I. E. (1963). Sketchpad: A man-machine graphical communication system. In *Proceedings of AFIPS'63* (pp. 329–346). ACM. <https://doi.org/10.1145/1461551.1461591>
- Svensson, B. & Keller, C. (2024). agentic relationship dynamics in human-AI collaboration: A study of interactions with GPT-based agentic information systems artifacts. In Bui T.X. (Ed.), *Proceedings Annual Hawaii International Conference on System Science* (pp. 7292–7301). IEEE Computer Society.
- Swan, M. & Dos Santos, R. P. (2023). Quantum intelligence: Responsible human-AI entities. In Kido T. and Takadama K. (Eds.), *CEUR Workshop Proceeding* (Vol. 3527, pp. 21–31). CEUR-WS.
- Söllner, M., Bittner, E., Ebel, P. A., & Oeste-Reiß, S. (2023). Applications of human-AI collaboration: Insights from theory and practice. In *Proceedings of the Annual Hawaii International Conference on System Sciences 2023-January* (p. 236). <https://doi.org/10.24251/HICSS.2023.028>
- Süße, M., Kobert, & C., Kries. (2021). Antecedents of constructive human-AI collaboration: An exploration of human actors' key competencies. In Camarinha-Matos L.M., Boucher X., Boucher X., and Afsarmanesh H. (Eds.), *IFIP Advances in Information and Communication Technology*, IFIPAICT (Vol. 629, pp. 113–124). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-85969-5\\_10](https://doi.org/10.1007/978-3-030-85969-5_10)
- Süße, T., Kobert, M., & Kries, C. (2023). Human-AI interaction in remanufacturing: Exploring shop floor workers' behavioural patterns within a specific human-AI system. *Labour and Industry*, 33(3), 344–363. <https://doi.org/10.1080/10301763.2023.2251103>
- Tag, B., van Berkel, N., Verma, S., Zhao, B. Z. H., Berkovsky, S., Kaafar, D., Kostakos, V., & Ohrimenko, O. (2023). DDodD: Dual denial of decision attacks on human-AI teams. *IEEE Pervasive Computing*, 22(1), 77–84. <https://doi.org/10.1109/MPRV.2022.3218773>
- Tamura, T., Ito, H., Oyama, S., & Morishima, A. (2024). Influence of AI's uncertainty in the Dawid-Skene aggregation for human-AI crowdsourcing. In Sserwanga I., Joho H., Ma J., Hansen P., Wu D., Koizumi M., and Gilliland A.J. (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 14598, pp. 232–247). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-57867-0\\_17](https://doi.org/10.1007/978-3-031-57867-0_17)
- Tan, C. S., Gupta, A., & Xu, C. (2022). Are two heads always better than one? Human-AI complementarity in multi-criteria order planning. In *IEEE Int. Conf. Ind. Eng. Eng. Manage.* (Vol. 2022-December, pp. 939–943). IEEE Computer Society. <https://doi.org/10.1109/IEEM55944.2022.9989949>
- Tavakoli, M., Faraji, A., Molavi, M., Mol, S. T., & Kismihók, G. (2022). Hybrid human-AI curriculum development for personalised informal learning environments. In *LAK22: 12th International Learning Analytics and Knowledge Conference (LAK22)* (pp. 563–569). Association for Computing Machinery. <https://doi.org/10.1145/3506860.3506917>
- Taze, D., HArtley, C., Morgan, A. W., Chakrabarty, A., Mackie, S. L., & Griffin, K. J. (2022). Developing consensus in histopathology: The role of the Delphi method. *Histopathology*, 81(2), 159–167. <https://doi.org/10.1111/his.14650>
- Tchemeube, R. B., Ens, J., Plut, C., Pasquier, P., Safi, M., Grabit, Y., & Rolland, J.-B. (2023). Evaluating human-AI interaction via usability, user experience and acceptance measures for MMM-C: A creative AI system for music composition. In Elkind E. (Ed.), *IJCAI Int. Joint Conf. Artif. Intell.* (Vol. 2023-August, pp. 5769–5778). International Joint Conferences on Artificial Intelligence.
- Tenhundfeld, N. L. (2023). Two birds with one stone: Writing a paper entitled “ChatGPT as a tool for studying human-AI interaction in the wild” with ChatGPT. In *Proc Hum Factors Ergon Soc.* (Vol. 67, No. 1). SAGE Publications Inc. <https://doi.org/10.1177/21695067231192916>
- Thieme, A., Cutrell, E., Morrison, C., Taylor, A., & Sellen, A. (2020). Interpretability as a dynamic of human-AI interaction. *Interactions*, 27(5), 40–45. <https://doi.org/10.1145/3411286>
- Thieme, C., & Utne, I. (2017). A risk model for autonomous marine systems and operation focusing on human-autonomy collaboration. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 231(4), 446–464. <https://doi.org/10.1177/1748006X17709377>
- Thomas, D. R., Lin, J., Gatz, E., Gurung, A., Gupta, S., Norberg, K., Fancsali, S. E., Aleven, V., Branstetter, L., Brunskill, E., & Koedinger, K. R. (2024). Improving student learning with hybrid human-AI tutoring: A three-study quasi-experimental investigation. In *Proceedings of the 14th Learning Analytics and Knowledge Conference (LAK '24)* (pp. 404–415). Association for Computing Machinery. <https://doi.org/10.1145/3636555.3636896>
- Tian, F. (2024). Building an instructional design model for human-AI collaboration grounded in activity theory. In *Proceedings of the 15th International Conference on Education Technology and Computers (ICETC '23)* (pp. 33–39). Association for Computing Machinery. <https://doi.org/10.1145/3629296.3629302>
- Tkiousat, Z., Labonté-LeMoyne, É., Titah, R., Saunier, N., Léger, P.-M., & Sénécal, S. (2022). Attention and human AI collaboration – The context of automated vehicles. In Stephanidis C., Antona M., Ntoa S., and Salvendy G. (Eds.), *Communications in computer and information science, CCIS* (Vol. 1655, pp. 702–706). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-19682-9\\_89](https://doi.org/10.1007/978-3-031-19682-9_89)
- Tran, M. T. (2024). A systematic literature review on the human-AI partnership roles in higher education. In *Enhancing and Predicting*

- Dig. *Consumer Behavior with AI* (pp. 28–38). IGI Global. <https://doi.org/10.4018/979-8-3693-4453-8.ch003>
- Tschopp, M., & Sassenberg, K. (2024). The impact of human-AI relationship perception on voice shopping intentions. *Human-Machine Communication*, 8, 101–117. <https://doi.org/10.30658/hmc.8.5>
- Tsiakas, K., & Murray-Rust, D. (2024). Unpacking human-AI interactions: From interaction primitives to a design space. *ACM Transactions on Interactive Intelligent Systems*, 14(3), 1–51. <https://doi.org/10.1145/3664522>
- Tuncer & Ramirez, A. (2022). exploring the role of trust during human-AI collaboration in managerial decision-making processes. In J. Y. Chen, G. Fragomeni, H. Degen, & S. Ntoa (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 13518, pp. 541–557). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-21707-4\\_39](https://doi.org/10.1007/978-3-031-21707-4_39)
- Turchi, S., Carta, L., Ambrosini, A., & Malizia. (2023). Human-AI co-creation: Evaluating the impact of large-scale text-to-image generative models on the creative process. In L. D. Spano, A. Schmidt, C. Santoro, & S. Stumpf (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 13917, pp. 35–51). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-34433-6\\_3](https://doi.org/10.1007/978-3-031-34433-6_3)
- Turoff, M. (1970). The design if a policy Delphi. *Technological Forecasting and Social Change*, 2(2), 149–171. [https://doi.org/10.1016/0040-1625\(70\)90161-7](https://doi.org/10.1016/0040-1625(70)90161-7)
- Tutul, A. A., Chaspari, T., Levitan, S. I., & Hirschberg, J. (2023). Human-AI collaboration for the detection of deceptive speech. In *Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos, ACIIW*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ACIIW59127.2023.10388114>
- Tutul, A. A., Nirjhar, E. H., & Chaspari, T. (2024). investigating trust in human-AI collaboration for a speech-based data analytics task. *International Journal of Human-Computer Interaction*, 41(5), 1–19. <https://doi.org/10.1080/10447318.2024.2328910>
- Tülübaş, T., Demirkol, M., Özdemir, T. Y., Polat, H., Karakose, T., & Yirci, R. (2023). An interview with ChatGPT on emergency remote teaching: A comparative analysis based on human-AI collaboration. *Educational Process International Journal*, 12(2), 93–110. <https://doi.org/10.22521/edupij.2023.122.6>
- Ueno, T., Sawa, Y., Kim, Y., Urakami, J., Oura, H., & Seaborn, K. (2022). Trust in human-AI interaction: Scoping out models, measures, and methods. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems (CHI EA '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491101.3519772>
- Ulfert, A.-S., Georganta, E., Centeio Jorge, C., Mehrotra, S., & Tielman, M. (2024). Shaping a multidisciplinary understanding of team trust in human-AI teams: A theoretical framework. *European Journal of Work and Organizational Psychology*, 33(2), 158–171. <https://doi.org/10.1080/1359432X.2023.2200172>
- Ulfert-Blank, A.-S., Georganta, E., Tielman, M., & Oron-Gilad, T. (2023). Piecing together the puzzle: Understanding trust in human-AI teams. In P. K. Murukannaiah & T. Hirzle (Eds.), *CEUR Workshop Proceeding* (Vol. 3456, pp. 169–174). CEUR-WS.
- van Berkel, N., Skov, M. B., & Kjeldskov, J. (2021). Human-AI interaction: Intermittent, continuous, and proactive. *Interactions*, 28(6), 67–71. <https://doi.org/10.1145/3486941>
- Van Dalen, H. P., & Henkens, K. (2012). Intended and unintended consequences of a publish-or-perish culture: A worldwide survey. *Journal of the American Society for Information Science and Technology*, 63(7), 1282–1293. <https://doi.org/10.1002/asi.22636>
- van den Bosch, K., Schoonderwoerd, T., Blankendaal, R., & Neerincx, M. (2019). Six Challenges for Human-AI Co-learning. In R. A. Sottilare & J. Schwarz (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 11597, pp. 572–589). Springer Verlag. [https://doi.org/10.1007/978-3-030-22341-0\\_45](https://doi.org/10.1007/978-3-030-22341-0_45)
- Van Rooy, K. Vaes. (2024). Harmonizing human-AI synergy: Behavioral science in AI-integrated design. In M. Storga, S. Skec, T. Martinec, D. Marjanovic, N. Pavkovic, & M. M. Skec (Eds.), *Proceeding Des. Soc.* (Vol. 4, pp. 2287–2296). Cambridge University Press. <https://doi.org/10.1017/pds.2024.231>
- van Zoelen, E. M., van den Bosch, K., Abbink, D., & Neerincx, M. (2023). Ontology-based reflective communication for shared human-AI recognition of emergent collaboration patterns. In R. Aydoğan, N. Criado, V. Sanchez-Anguix, J. Lang, & M. Serramia (Eds.), *Lecture Notes in Computer Science, LNAI* (Vol. 13753, pp. 621–629). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-21203-1\\_40](https://doi.org/10.1007/978-3-031-21203-1_40)
- Varshini Devi, I. R., Oviya., & K., Raja. (2024). EMPATHIC: Emulating human-like multimodal personality architecture through thoughtful human-AI conversation. In S. Thakur, R. Garg, A. Singhal, S. Kumar, S. Kumar, R. Arora, & Sehgal R. Kaushik (Eds.), *Proceeding Int. Conf. Cloud Comput., Data Sci. Eng., Conflu.* (pp. 79–85). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/Confluence60223.2024.10463330>
- Vassilakopoulou, P., Haug, A., Salvesen, L. M., & Pappas, I. O. (2023). Developing human/AI interactions for chat-based customer services: Lessons learned from the Norwegian government. *European Journal of Information Systems*, 32(1), 10–22. <https://doi.org/10.1080/0960085X.2022.2096490>
- Veitch, E. & Alsos, O. A. (2022). A systematic review of human-AI interaction in autonomous ship systems. *Safety Science*, 152, 105778. <https://doi.org/10.1016/j.ssci.2022.105778>
- Villareale, J., Cimolino, G., & Gomme, D. (2023). Playing with Dezzo: Adapting human-AI interaction to the context of play. In *Proceedings of the 18th International Conference on the Foundations of Digital Games (FDG '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3582437.3587198>
- Viros-I-Martin, A. & Selva, D. (2021). A framework to study human-AI collaborative design space exploration. In *Proceeding ASME Des. Eng. Tech. Conf.* (Vol. 6). American Society of Mechanical Engineers (ASME). <https://doi.org/10.1115/DETC2021-67619>
- Virvou, M. & Tsihrintzis, G. A. (2023). Pre-made empowering artificial intelligence and ChatGPT: The growing importance of human AI-experts. In *Int. Conf. Inf., Intell., Syst. Appl., IISA*. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/IISA59645.2023.10345880>
- Vodrahalli, K., Daneshjou, R., Gerstenberg, T., & Zou, J. (2022). Do humans trust advice more if it comes from AI? An analysis of human-AI interactions. In *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society (AI/ES '22)* (pp. 763–777). Association for Computing Machinery. <https://doi.org/10.1145/3514094.3534150>
- Vodrahalli, K., Gerstenberg, T., & Zou, J. (2022). Uncalibrated models can improve human-AI collaboration. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, & A. Oh (Eds.), *Advances in neural information processing systems* (Vol. 35). Neural Information Processing Systems Foundation.
- Vold, K. (2024). Human-AI cognitive teaming: Using AI to support state-level decision making on the resort to force. *Australian Journal of International Affairs*, 78(2), 229–236. <https://doi.org/10.1080/10357718.2024.2327383>
- Vorm, E. S. (2020). Computer-centered humans: Why human-AI interaction research will be critical to successful AI integration in the DoD. *IEEE Intelligent Systems*, 35(4), 112–116. <https://doi.org/10.1109/MIS.2020.3013133>
- Voudouris, K., Crosby, M., Beyret, B., Hernández-Orallo, J., Shanahan, M., Halina, M., & Cheke, L. G. (2022). Direct human-AI comparison in the animal-AI environment. *Frontiers in Psychology*, 13, 711821. <https://doi.org/10.3389/fpsyg.2022.711821>
- Vuppapapati, A., Ilapakurti, S., Kedari, R., Vuppapapati, J., & Kedari, S. (2020). Human AI symbiosis: The role of artificial intelligence in stratifying high-risk outpatient senior citizen fall events in a non-connected environments. In T. Ahram, W. Karwowski, A. Vergnano, F. Leali, & R. Taiar (Eds.), *Adv. Intell. Sys. Comput., AISC* (Vol. 1131, pp. 325–332). Springer. [https://doi.org/10.1007/978-3-030-39512-4\\_52](https://doi.org/10.1007/978-3-030-39512-4_52)
- Vössing, M., Köhl, N., Lind, M., & Satzger, G. (2022). Designing transparency for effective human-AI collaboration. *Information Systems Frontiers*, 24(3), 877–895. <https://doi.org/10.1007/s10796-022-10284-3>

- Waeffer, U Schmid. (2020). Explainability is not enough: Requirements for human-AI-partnership in complex socio-technical systems. In F. Matos (Ed.), *Proceeding Eur. Conf. Impact Artif. Intell. Robot., ECAIR* (pp. 185–193). Academic Conferences International. <https://doi.org/10.34190/EAIR.20.007>
- Wallinheimo, A.-S., Evans, S. L., & Davitti, E. (2023). Training in new forms of human-AI interaction improves complex working memory and switching skills of language professionals. *Frontiers in Artificial Intelligence*, 6, 1253940. <https://doi.org/10.3389/fraci.2023.1253940>
- Wan, Q., Hu, S., Zhang, Y., Wang, P., Wen, B., & Lu, Z. (2024). It felt like having a second mind: Investigating human-AI co-creativity in prewriting with large language models. *Proceedings of the ACM on Human-Computer Interaction*, 8(CSCW1), 1–26. <https://doi.org/10.1145/3637361>
- Wang, B. (2023). Democratizing content creation and consumption through human-AI copilot systems. In *Adjunct Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23 Adjunct)*. Association for Computing Machinery. <https://doi.org/10.1145/3586182.3616707>
- Wang, B., Yuan, T., & Rau, P.-L. P. (2024). Effects of explanation strategy and autonomy of explainable AI on human-AI collaborative decision-making. *International Journal of Social Robotics*, 16(4), 791–810. <https://doi.org/10.1007/s12369-024-01132-2>
- Wang, D., Weisz, J. D., Muller, M., Ram, P., Geyer, W., Dugan, C., Tausczik, Y., Samulowitz, H., & Gray, A. (2019). Human-AI collaboration in data science: Exploring Data Scientists' perceptions of automated AI. *Proceedings of the ACM on Human-Computer Interaction*, 3(CSCW), 1–24. <https://doi.org/10.1145/3359313>
- Wang, F., Liu, X., Liu, O., Neshati, A., Ma, T., Zhu, M., & Zhao, J. (2023). Slide4N: Creating presentation slides from computational notebooks with human-AI collaboration. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3580753>
- Wang, P. (2019). On defining artificial intelligence. *Journal of Artificial General Intelligence*, 10(2), 1–37. <https://doi.org/10.2478/jagi-2019-0002>
- Wang, P., & Ding, H. (2024). The rationality of explanation or human capacity? Understanding the impact of explainable artificial intelligence on human-AI trust and decision performance. *Information Processing & Management*, 61(4), 103732. <https://doi.org/10.1016/j.ipm.2024.103732>
- Wang, Q., Saha, K., Gregori, E., Joyner, D., & Goel, A. (2021). Towards mutual theory of mind in human-AI interaction: How language reflects what students perceive about a virtual teaching assistant. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery. <https://doi.org/10.1145/3411764.3445645>
- Wang, S., Menon, S., Long, T., Henderson, K., Li, D., Crowston, K., Hansen, M., Nickerson, J. V., & Chilton, L. B. (2024). ReelFramer: Human-AI co-creation for news-to-video translation. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642868>
- Wang, S., Nan, Y., Zhang, S., Felder, F., Xing, X., Fang, Y., Del Ser, J., Walsh, S. L. F., & Yang, G. (2024). Probing perfection: The relentless art of meddling for pulmonary airway segmentation from HRCT via a human-AI collaboration based active learning method. *Artificial Intelligence in Medicine*, 154, 102930. <https://doi.org/10.1016/j.artmed.2024.102930>
- Wang, S., Ning, Z., Truong, A., Dontcheva, M., Li, D., & Chilton, L. B. (2024). PodReels: Human-AI co-creation of video podcast teasers. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference (DIS '24)* (pp. 958–974). Association for Computing Machinery. <https://doi.org/10.1145/3643834.3661591>
- Wang, X., Liu, Q., Pang, H., Tan, S. C., Lei, J., Wallace, M. P., & Li, L. (2023). What matters in AI-supported learning: A study of human-AI interactions in language learning using cluster analysis and epistemic network analysis. *Computers & Education*, 194, 104703. <https://doi.org/10.1016/j.compedu.2022.104703>
- Wang, X. & Yin, M. (2021). Are explanations helpful? A comparative study of the effects of explanations in AI-assisted decision-making. In *IUI '21: Proceedings of the 26th International Conference on Intelligent User Interfaces* (pp. 318–328). ACM, College Station. <https://doi.org/10.1145/3397481.3450650>
- Weber, S., Kordyaka, B., Palombo, R., Siemon, D., & Niehaves, B. (2023). Is a fool with a(n AI) tool still a fool? An empirical study of the creative quality of human-AI collaboration. In *International Conference on Information Systems, ICIS: "Rising like Phoenix: Emerg. Pandemic Reshaping Hum. Endeavors Digit. Technol.* Association for Information Systems.
- Weekes, T. R., & Eskridge, T. C. (2022). Design thinking the human-AI experience of neurotechnology for knowledge workers. In M. Kurosu, S. Yamamoto, H. Mori, D. D. Schmorow, C. M. Fidopiastis, N. A. Streitz, & S. Konomi (Eds.), *Lecture Notes in Computer Science, LNCS* (Vol. 13519, pp. 527–545). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-17618-0\\_37](https://doi.org/10.1007/978-3-031-17618-0_37)
- Weerawardhana, S., Akintunde, M., & Moreau, L. (2024). exploring the dynamic nature of trust using interventions in a human-AI collaborative task. In F. Lorig, J. Tucker, A. D. Lindstrom, F. Dignum, P. Murukannaiah, A. Theodorou, & P. Yolum (Eds.), *Frontiers in artificial intelligence and applications* (Vol. 386, pp. 335–349). IOS Press BV. <https://doi.org/10.3233/FAIA240206>
- Wei, Y., Lu, W., Cheng, Q., Jiang, T., & Liu, S. (2022). How humans obtain information from AI: Categorizing user messages in human-AI collaborative conversations. *Information Processing & Management*, 59(2), 102838. <https://doi.org/10.1016/j.ipm.2021.102838>
- Weijers & Munn, N. (2022). Human-AI friendship: Rejecting the appropriate sentimentality criterion. In *Stud. Appl. Philos. Epistemol. Ration. Ethics* (Vol. 63, pp. 209–223). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-09153-7\\_17](https://doi.org/10.1007/978-3-031-09153-7_17)
- Weisz, J. D., Muller, M., Houde, S., Richards, J., Ross, S. I., Martinez, F., Agarwal, M., & Talamadupula, K. (2021). Perfection not required? Human-AI partnerships in code translation. In *Proceedings of the 26th International Conference on Intelligent User Interfaces (IUI '21)* (pp. 402–412). Association for Computing Machinery. <https://doi.org/10.1145/3397481.3450656>
- Wellsandt, S., Foosherian, M., Bousdekis, A., Lutzer, B., Paraskevopoulos, F., Verginadis, Y., & Mentzas, G. (2023). Fostering human-AI collaboration with digital intelligent assistance in manufacturing SMEs. In E. Alfnes, A. Romsdal, J. O. Strandhagen, G. von Cieminski, & D. Romero (Eds.), *IFIP Advances in Information and Communication Technology, AICT* (Vol. 689, pp. 649–661). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-031-43662-8\\_46](https://doi.org/10.1007/978-3-031-43662-8_46)
- Westby, S., & Riedl, C. (2023). Collective intelligence in human-AI teams: A Bayesian theory of mind approach. In Williams B., Chen Y., and Neville J. (Eds.), *Proceeding AAAI Conf. Artif. Intell., AAAI* (Vol. 37, pp. 6119–6127). AAAI Press.
- Westphal, M., Vössing, M., Satzger, G., Yom-Tov, G. B., & Rafaeli, A. (2023). Decision control and explanations in human-AI collaboration: Improving user perceptions and compliance. *Computers in Human Behavior*, 144, 107714. <https://doi.org/10.1016/j.chb.2023.107714>
- Wiegrefe, S., Hessel, J., Swayamdipta, S., Riedl, M., & Choi, Y. (2022). Reframing human-AI collaboration for generating free-text explanations. In *NAACL—Conf. N. Am. Chapter Assoc. Comput. Linguist.: Hum. Lang. Technol., Proceeding Conf.* (pp. 632–658). Association for Computational Linguistics (ACL).
- Wienrich, C., & Latoschik, M. E. (2021). eXtended Artificial Intelligence: New Prospects of Human-AI Interaction Research. *Frontiers in Virtual Reality*, 2, 686783. <https://doi.org/10.3389/frvir.2021.686783>
- Wienrich, C., Latoschik, M. E., & Obremski, D. (2024). Gender Differences and Social Design in Human-AI Collaboration: Insights from Virtual Cobot Interactions Under Varying Task Loads. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3650827>



- Williams, M.-A. (2019). The Artificial Intelligence race: Will Australia lead or lose? *Journal & Proceedings of the Royal Society of New South Wales*, 152(1), 105–114. <https://doi.org/10.5962/p.361856>
- Wischniewski, M., Krämer, N., & Müller, E. (2023). Measuring and Understanding Trust Calibrations for Automated Systems: A Survey of the State-Of-The-Art and Future Directions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. ACM. <https://doi.org/10.1145/3544548.3581197>
- Wittmann, M., & Morschheuser, B. (2022). What do games teach us about designing effective human-AI cooperation? – A systematic literature review and thematic synthesis on design patterns of non-player characters. In *CEUR Workshop Proceeding*, Bujic M., Koivisto J., and Hamari J. (Eds.), Vol. 3147. CEUR-WS. 95–104.
- Wu, T., Terry, M., & Cai, C. J. (2022). AI Chains: Transparent and Controllable Human-AI Interaction by Chaining Large Language Model Prompts. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3517582>
- Wu, Y., Kim, K. J., & Mou, Y. (2022). Minority social influence and moral decision-making in human-AI interaction: The effects of identity and specialization cues. *New Media & Society*, 26(10), 5619–5637. <https://doi.org/10.1177/14614448221138072>
- Wu, Z., Ji, D., Yu, K., Zeng, X., Wu, D., & Shidujaman, M. (2021). AI creativity and the human-AI Co-creation Model. In M. Kurosu (Ed.), *Lect. Notes Comput. Sci.* (Vol. 12762 LNCS, pp. 171–190). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-78462-1\\_13](https://doi.org/10.1007/978-3-030-78462-1_13)
- Wu, Z., Li, Y., Ji, D., Wu, D., Shidujaman, M., Zhang, Y., & Zhang, C. (2022). Human-AI Co-Creation of Art Based on the Personalization of Collective Memory. In *Proceeding Asian Conf. Artif. Intell. Technol.*, ACAIT. Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ACAIT56212.2022.10137839>
- Xie, Y., Zhu, K., Zhou, P., & Liang, C. (2023). How does anthropomorphism improve human-AI interaction satisfaction: A dual-path model. *Computers in Human Behavior*, 148, 107878. <https://doi.org/10.1016/j.chb.2023.107878>
- Xu, Z., Cai, E. T. K., Lim, X., Song, A., Chong, C.-W., Tan., & J., Yu. (2020). Artificial intelligence or augmented intelligence: A case study of Human-AI collaboration in operational decision making. In *Proceeding Pac. Asia Conf. Inf. Syst.: Inf. Syst. (IS) Future*, PACIS. Association for Information Systems.
- Xu, C., & Ge, X. (2024). AI as a child of mother earth: Regrounding human-AI interaction in ecological thinking. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3644065>
- Xu, C., Lien, K.-C., & Höllerer, T. (2023). Comparing zealous and restrained AI recommendations in a real-world human-AI collaboration task. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. ACM. <https://doi.org/10.1145/3544548.3581282>
- Xu, C., Lien, K.-C., & Höllerer, T. (2023). Comparing zealous and restrained AI recommendations in a real-world human-AI collaboration task. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3581282>
- Xu, W., & Gao, Z. (2024). Applying HCAI in developing effective human-AI teaming: A perspective from human-AI joint cognitive systems. *Interactions*, 31(1), 32–37. <https://doi.org/10.1145/3635116>
- Xu, Z., Hong, C., Soria Zurita, N. F., Gyory, J. T., Stump, G., Nolte, H., Cagan, J., & McComb, C. (2023). Adaptation and challenges in human-AI partnership for the design of complex engineering systems. In *Proceeding ASME Des. Eng. Tech. Conf.*, Vol. 3B. American Society of Mechanical Engineers (ASME). <https://doi.org/10.1115/DETC2023-115176>
- Yan, L., Echeverria, V., Fernandez-Nieto, G. M., Jin, Y., Swiecki, Z., Zhao, L., Gašević, D., & Martinez-Maldonado, R. (2024). Human-ai collaboration in thematic analysis using ChatGPT: A user study and design recommendations. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613905.3650732>
- Yan, X., Guo, J., Lou, X., Wang, J., Zhang, H., & Du, Y. (2023). An efficient end-to-end training approach for zero-shot human-AI coordination. In A. Oh, T. Neumann, A. Globerson, K. Saenko, M. Hardt, & S. Levine (Eds.), *Advances in neural information processing systems*, Vol. 36. Neural information processing systems foundation.
- Yang, Y., Zhou, Z., Zhang, T. J.-J., Li., & L. C., Ray. (2022). AI as an active writer: Interaction strategies with generated text in human-AI collaborative fiction writing. In A. Smith-Renner & O. Amir (Eds.), *CEUR Workshop Proceeding* (Vol. 3124, pp. 56–65). CEUR-WS. <https://ceur-ws.org/Vol-3124/paper6.pdf>
- Yang, K. B., Lawrence, L. E. M., Echeverria, V., Guo, B., Rummel, N., & Aleven, V. (2021). Surveying teachers' preferences and boundaries regarding human-AI control in dynamic pairing of students for collaborative learning. In T. De Laet, R. Klemke, C. Alario-Hoyos, I. Hilliger, & A. Ortega-Arranz (Eds.), *Lecture Notes in Computer Science* (Vol. 12884 LNCS, pp. 260–274). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-3-030-86436-1\\_20](https://doi.org/10.1007/978-3-030-86436-1_20)
- Yang, K. B., Echeverria, V., Lu, Z., Mao, H., Holstein, K., Rummel, N., & Aleven, V. (2023). Pair-up: Prototyping human-AI co-orchestration of dynamic transitions between individual and collaborative learning in the classroom. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3581398>
- Yang, Q., Steinfeld, A., Rosé, C., & Zimmerman, J. (2020). Re-examining whether, why, and how human-AI interaction is uniquely difficult to design. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)* (pp. 1–13). Association for Computing Machinery. <https://doi.org/10.1145/3313831.3376301>
- Yang, S., Xie, W., Chen, Y., Li, Y., Jiang, H., & Zhou, W. (2024). Warmth or competence? Understanding voice shopping intentions from Human-AI interaction perspective. *Electronic Commerce Research*. <https://doi.org/10.1007/s10660-024-09859-w>
- Yang, Y., Zhang, L., Xu, G., Ren, G., & Wang, G. (2024). An evidence-based multimodal fusion approach for predicting review helpfulness with human-AI complementarity. *Expert Systems with Applications*, 238, 121878. <https://doi.org/10.1016/j.eswa.2023.121878>
- Yao, D., Holopainen, J., & Laukkanen, T. (2024). Human-AI interaction—Is it trust or emotions that mediates behavioral intentions?. In *Proceedings Annual Hawaii International Conference on System Science* (pp. 1448–1455), Bui T.X. (Ed.). IEEE Computer Society.
- Yasser, A., & Abu-Elkhiar, M. (2022). Towards fluid software architectures: Bidirectional human-AI interaction. In *Proceedings of the 36th IEEE/ACM International Conference on Automated Software Engineering (ASE '21)* (pp. 1368–1372) IEEE Press. <https://doi.org/10.1109/ASE51524.2021.9678647>
- Yildirim, N., Pushkarna, M., Goyal, N., Wattenberg, M., & Viégas, F. (2023). Investigating how practitioners use human-AI guidelines: A case study on the people + AI guidebook. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3544548.3580900>
- Yiwen, L., Yahui, Y., Jinrong, F., Tao, F., Ting, Y., Yingxi, X., Yanxia, G., Taiguo, Q., & Xian, Z. (2024). Human-AI collaboration: A study on anti-ChatGPT strategies employed in innovative practical homework towards “One-Click-Answer” issue in AIGC. In W. Hong & G. Kanaparan (Eds.), *Communications in computer and information science* (Vol. 2025 CCIS, pp. 343–353). Springer Science and Business Media Deutschland GmbH. [https://doi.org/10.1007/978-981-97-0737-9\\_30](https://doi.org/10.1007/978-981-97-0737-9_30)
- You, D. L. (2022). Towards stronger adversarial baselines through human-AI collaboration. In T. Shavrina, V. Mikhailov, V. Malykh, E. Artemova, O. Serikov, & V. Protasov (Eds.), *NLP-Power—Workshop Effic. Benchmarking NLP, Proceeding Workshop* (pp. 11–21). Association for Computational Linguistics (ACL). <https://doi.org/10.18653/v1/2022.nlp-power-1.2>
- Yu, R., Lee, S., Xie, J., Billah, S. M., & Carroll, J. M. (2024). Human-AI collaboration for remote sighted assistance: Perspectives from the LLM era. *Future Internet*, 16(7), 254. <https://doi.org/10.3390/fi16070254>

- Yu, Y., Yu, H., Cho, J., Park, J., Lim, E., & Ha, J. (2022). Human-AI co-creation practice to reconfigure the cultural emotion: Han. In *Proceedings of the 2022 ACM Conference on Information Technology for Social Good (GoodIT '22)* (pp. 414–417). Association for Computing Machinery. <https://doi.org/10.1145/3524458.3547127>
- Yue, B., & Li, H. (2023). The impact of human-AI collaboration types on consumer evaluation and usage intention: A perspective of responsibility attribution. *Frontiers in Psychology*, 14, 1277861. <https://doi.org/10.3389/fpsyg.2023.1277861>
- Zeng, X., La Barbera, D., Roitero, K., Zubiaga, A., & Mizzaro, S. (2024). Combining large language models and crowdsourcing for hybrid human-AI misinformation detection. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '24)* (pp. 2332–2336). Association for Computing Machinery. <https://doi.org/10.1145/3626772.3657965>
- Zeng, Z., Wang, J., & He, N. (2022). Wind of bamboo: A chinese handwriting mingling interactive installation based on human-AI collaborative font design. In *Proceeding—IEEE VIS Arts Program, VISAP*. Institute of Electrical and Electronics Engineers Inc., 80–93. <https://doi.org/10.1109/VISAP57411.2022.00018>
- Zerick, J., Kaufman, Z., Ott, J., Kubler, J., Chow, E., Shah, S., & Lewis, G. (2024). *It Takes Two to Trust: Mediating Human-AI Trust for Resilience and Reliability* [Paper presentation]. In 2024 IEEE Conference on Artificial Intelligence (CAI), pp. 755–761. <https://doi.org/10.1109/CAI59869.2024.00145>
- Zhang, D., Huang, Y., Zhang, Y., & Wang, D. (2020). Crowd-assisted disaster scene assessment with human-AI interactive attention. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 34 (03), 2717–2724. <https://doi.org/10.1609/aaai.v34i03.5658>
- Zhang, G., Chong, L., Kotovsky, K., & Cagan, J. (2023). Trust in an AI versus a Human teammate: The effects of teammate identity and performance on Human-AI cooperation. *Computers in Human Behavior*, 139, 107536. <https://doi.org/10.1016/j.chb.2022.107536>
- Zhang, H., He, Y., Wu, X., Huang, P., Qin, W., Wang, F., Ye, J., Huang, X., Liao, Y., Chen, H., Guo, L., Shi, X., & Luo, L. (2023). PathNarratives: Data annotation for pathological human-AI collaborative diagnosis. *Frontiers in Medicine*, 9, 1070072. <https://doi.org/10.3389/fmed.2022.1070072>
- Zhang, Q., Lee, M. L., & Carter, S. (2022). You complete me: Human-AI teams and complementary expertise. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3517791>
- Zhang, R., Duan, W., Flathmann, C., McNeese, N., Freeman, G., & Williams, A. (2023). Investigating AI teammate communication strategies and their impact in human-AI teams for effective teamwork. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW2), 1–31. <https://doi.org/10.1145/3610072>
- Zhang, R., Flathmann, C., Musick, G., Schelble, B., McNeese, N. J., Knijnenburg, B., & Duan, W. (2024). I know this looks bad, but i can explain: Understanding when AI should explain actions in human-AI teams. *ACM Transactions on Interactive Intelligent Systems*, 14(1), 1–23. <https://doi.org/10.1145/3635474>
- Zhang, R., McNeese, N. J., Freeman, G., & Musick, G. (2021). “An ideal human”: Expectations of AI teammates in human-AI teaming. *Proceedings of the ACM on Human-Computer Interaction*, 4(CSCW3), 1–25. <https://doi.org/10.1145/3432945>
- Zhang, S., Yu, J., Xu, X., Yin, C., Lu, Y., Yao, B., Tory, M., Padilla, L. M., Caterino, J., Zhang, P., & Wang, D. (2024). Rethinking human-AI collaboration in complex medical decision making: A case study in sepsis diagnosis. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery. <https://doi.org/10.1145/3613904.3642343>
- Zhang, X., Wei, X., Ou, C. X. J., Caron, E., Zhu, H., & Xiong, H. (2022). From Human-AI confrontation to human-AI symbiosis in Society 5.0: Transformation challenges and mechanisms. *IT Professional*, 24(3), 43–51. <https://doi.org/10.1109/MITP.2022.3175512>
- Zhang, G., Xia, M., Levy, S., & Dixon. (2021). COSMIC: A conversational interface for human-AI music co-creation [Paper presentation]. In *Proceeding Int. Conf. New Interfaces Music. Expr., International Conference on New Interfaces for Musical Expression*. <https://doi.org/10.21428/92fbbeb44.110a7a32>
- Zhang, Z., Gao, J., Dhaliwal, R. S., & Li, T. J.-J. (2023). VISAR: A human-AI argumentative writing assistant with visual programming and rapid draft prototyping. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3586183.3606800>
- Zhang, Z. J., Kaushik, S., Seo, J., Yuan, H., Das, S., Findlater, L., Gurari, D., Stangl, A., & Wang, Y. (2023). *ImageAlly: A Human-AI Hybrid Approach to Support Blind People in Detecting and Redacting Private Image Content* [Paper presentation]. In *Proceeding Symp. Usable Priv. Secur., SOUPS, USENIX Association*, pp 417–436.
- Zhang, Z., Ning, Z., Xu, C., Tian, Y., & Li, T. J.-J. (2023). PEANUT: A human-AI collaborative tool for annotating audio-visual data. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23)*. Association for Computing Machinery. <https://doi.org/10.1145/3586183.3606776>
- Zhang, Z., Xu, Y., Wang, Y., Yao, B., Ritchie, D., Wu, T., Yu, M., Wang, D., & Li, T. J.-J. (2022). StoryBuddy: A human-AI collaborative chatbot for parent-child interactive storytelling with flexible parental involvement. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3517479>
- Zhang, Z. T., Liu, Y., & Hussmann, H. (2021). Forward reasoning decision support: Toward a more complete view of the human-AI interaction design space. In *Proceedings of the 14th Biannual Conference of the Italian SIGCHI Chapter (CHIItaly '21)*. Association for Computing Machinery. <https://doi.org/10.1145/3464385.3464696>
- Zhao, M., Simmons, R., & Admoni, H. (2022). The role of adaptation in collective human-AI teaming. *Topics in Cognitive Science*. <https://doi.org/10.1111/tops.12633>
- Zhao, R., Song, J., Yuan, Y., Hu, H., Gao, Y., Wu, Y., Sun, Z., & Yang, W. (2023). Maximum entropy population-based training for zero-shot human-AI coordination. In Williams B., Chen Y., and Neville J. (Eds.), *Proceeding AAAI Conf. Artif. Intell., AAAI*. (Vol. 37, pp. 6145–6153). AAAI Press. <https://doi.org/10.1609/aaai.v37i5.25758>
- Zhao, X., Liu, J., Yu, Z., & Guo, B. (2024). HADT: Human-AI diagnostic team via hierarchical reinforcement learning. In S. Shekhar, V. Papalexakis, J. Gao, Z. Jiang, & M. Riondato (Eds.), *Proceeding SIAM Int. Conf. Data Min., SDM* (pp. 860–868). Society for Industrial and Applied Mathematics Publications. <https://doi.org/10.1137/1.9781611978032.98>
- Zhao, Y., Zhu, Z., Chen, B., & Qiu, S. (2023). Leveraging human-AI collaboration in crowd-powered source search: A preliminary study. *Journal of Social Computing*, 4(2)(2023), 95–111. <https://doi.org/10.23919/JSC.2023.0002>
- Zhao, Z., & Ma, X. (2018). A compensation method of two-stage image generation for human-ai collaborated in-situ fashion design in augmented reality environment. In *Proceeding—IEEE Int. Conf. Artif. Intell. Virtual Real., AIVR* (pp. 76–83). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/AIVR.2018.00018>
- Zheng, Q., Tang, Y., Liu, Y., Liu, W., & Huang, Y. (2022). UX research on conversational human-AI interaction: A literature review of the ACM Digital Library. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery. <https://doi.org/10.1145/3491102.3501855>
- Zheng, S. (2023). StyleGAN-Canvas: Augmenting StyleGAN3 for real-time Human-AI Co-Creation. In A. Smith-Renner & P. Taele (Eds.), *CEUR Workshop Proceeding* (Vol. 3359, pp. 108–120). CEUR-WS.
- Zhong, J., & Zheng, Y. (2023). Identifying the impact of Human-AI co-creation on students' creativity development: A conceptual framework. In *Int. Conf. Educ. Technol., ICET*. (pp. 66–70). Institute of Electrical and Electronics Engineers Inc. <https://doi.org/10.1109/ICET59358.2023.10424147>
- Zhu, H., Zhou, X., & Liu, H. (2024). Human-AI co-creation for intangible cultural heritage dance: Cultural genes retaining and innovation. In C. Stephanidis, M. Antona, S. Ntoa, and G. Salvendy (Eds.), Vol. 2116, *Communications in computer and information*

*science* CCIS (pp. 426–433). Springer. [https://doi.org/10.1007/978-3-031-61950-2\\_46](https://doi.org/10.1007/978-3-031-61950-2_46)

Ziegler, J., & Donkers, T. (2024). From explanations to human-AI co-evolution: Charting trajectories towards future user-centric AI. *i-com*, 23(2), 263–272. <https://doi.org/10.1515/icom-2024-0020>

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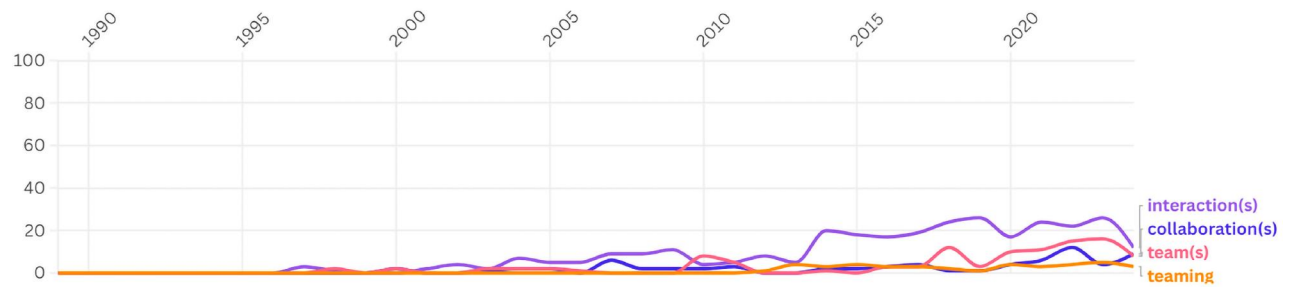
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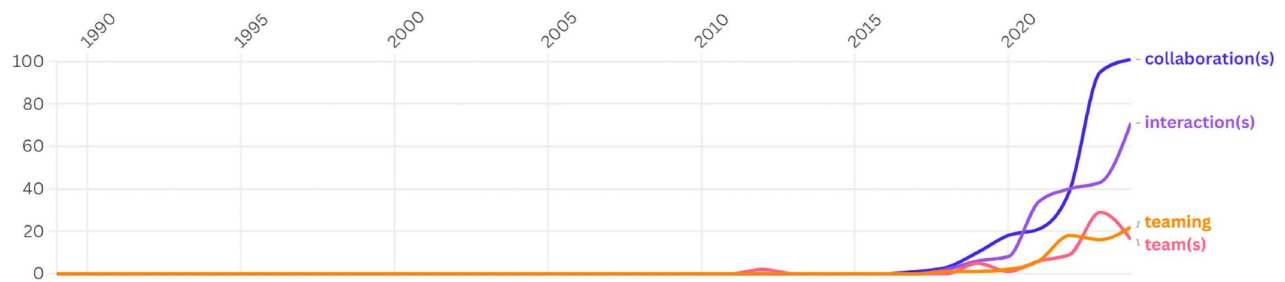
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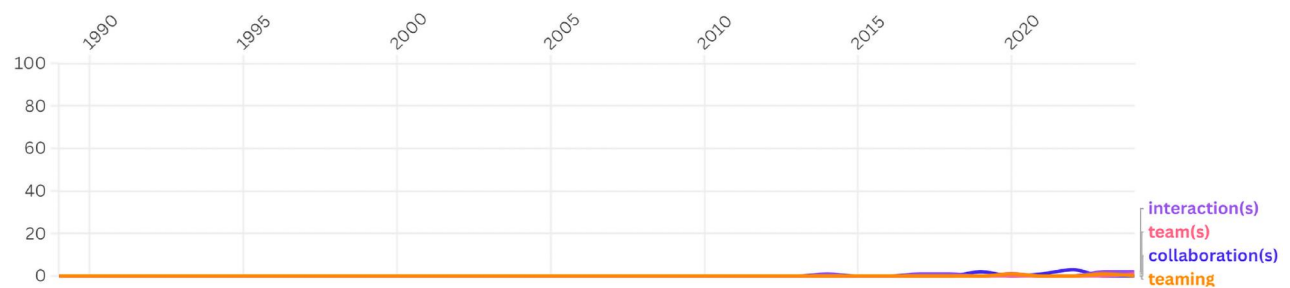
## Appendix A. Additional figures



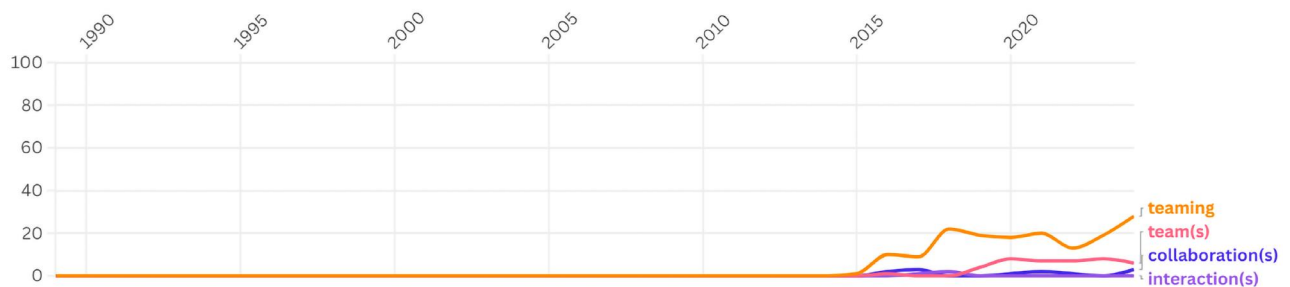
(a) Development of terminology using human-*agent* combinations, e.g., “human agent interaction”.



(b) Development of terminology using human-*AI* combinations, e.g., “human ai interaction”.

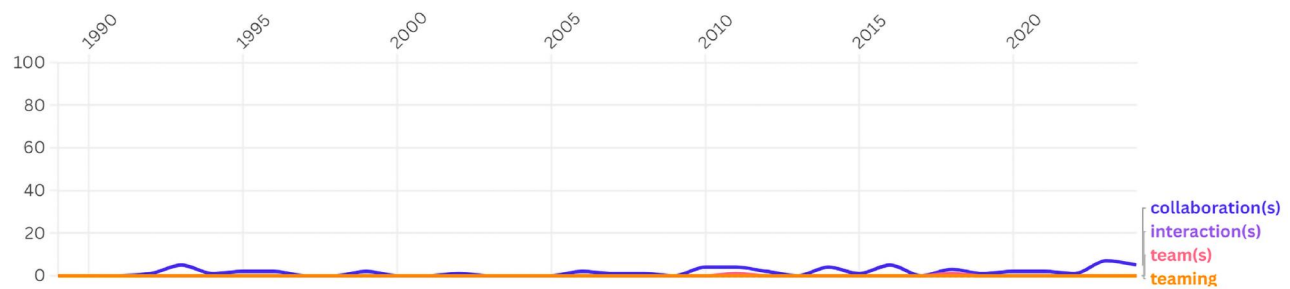


(c) Development of terminology using human-*algorithm* combinations, e.g., “human algorithm interaction”.

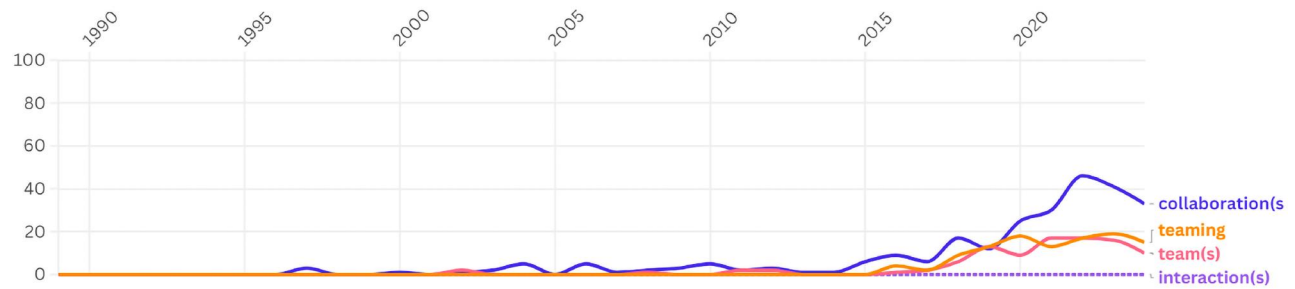


(d) Development of terminology using human-*autonomy* combinations, e.g., “human autonomy interaction”.

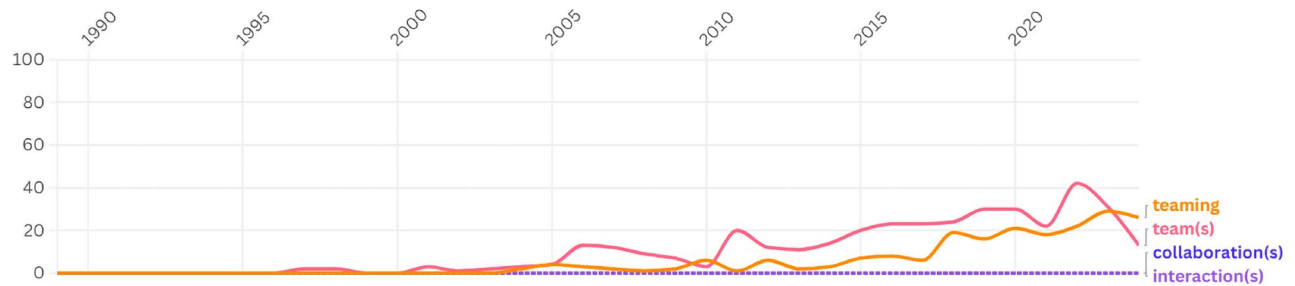
**Figure A1.** Historical development of terminology usage with different alternative terms that may refer to AI, ranging from 1989 to 2024. Values show publication counts for three-part compounds of “human”, alternative AI terms, and the key supplementary terms introduced in [Section 1](#).



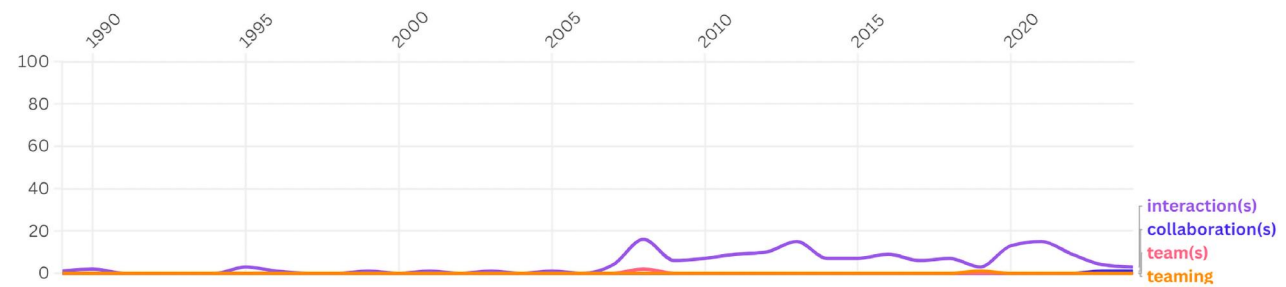
(e) Development of terminology using human-*computer* combinations, e.g., “human computer interaction”.



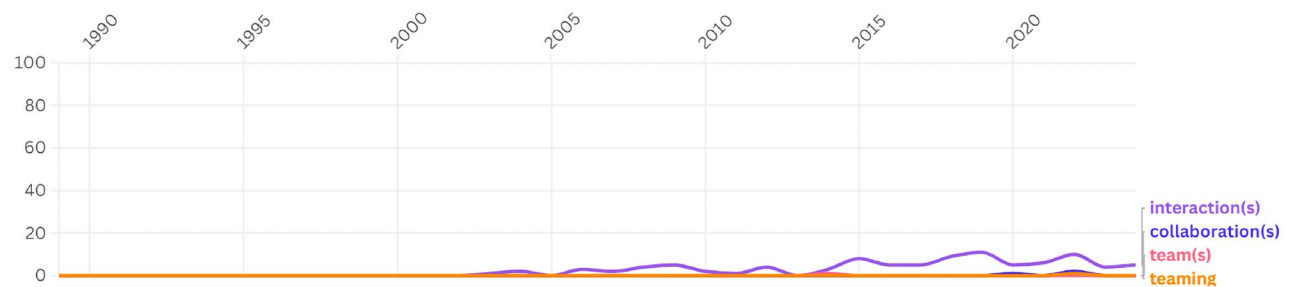
(f) Development of terminology using human-*machine* combinations, e.g., “human machine interaction”.



(g) Development of terminology using human-*robot* combinations, e.g., “human robot interaction”.

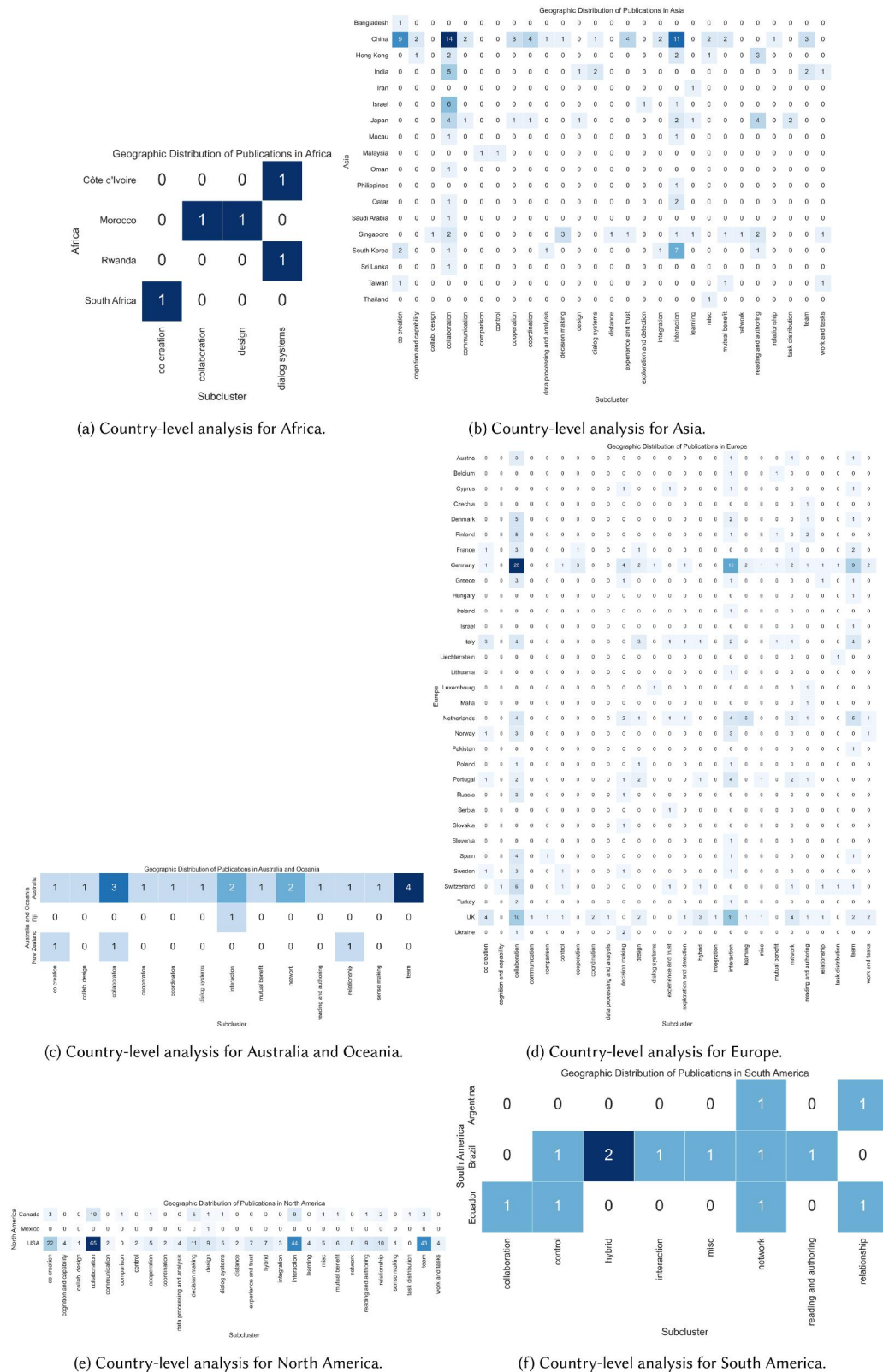


(h) Development of terminology using human-*system* combinations, e.g., “human system interaction”.



(i) Development of terminology using human-*technology* combinations, e.g., “human technology interaction”.

Figure A1. Continued.



**Figure A2.** Geographic distribution of human-AI terminology on country-level, per continent. Only countries and subclusters with publication counts > 0 are considered.



## Appendix B. Additional tables

**Table B1.** Overview of all clusters, subclusters, individual terms and the included publications.

Cluster	Subcluster	Term	Publications
Connection	Team	HAI Team	(Andrews et al., 2023; Babbar et al., 2022; Bansal et al., 2019b; Bendell et al., 2021; Bruni, 2024; Carolina Centeio et al., 2022; Cummings et al., 2021; de Visser et al., 2023; Endsley, 2023; Flathmann et al., 2023; 2024; Frattolillo et al., 2024; Georganta & Ulfert, 2024; Hagemann et al., 2023; Harris-Watson et al., 2023; Hauptman et al., 2024; Hou et al., 2025; Kraus et al., 2023; Lemmer et al., 2023; Liang et al., 2019; Munyaka et al., 2023; Naser & Bhattacharya, 2023; Schelble et al., 2023; Siu et al., 2021; Tag et al., 2023; Ulfert et al., 2024; Ulfert-Blank et al., 2023; Westby & Riedl, 2023; Zhang, Lee, et al., 2022; Zhang, Duan, et al., 2023; Zhang, Flathmann, et al., 2024)
		HAI Teaming	(Amresh et al., 2023; Andre et al., 2023; Attig et al., 2024; Baruwai Chhetri et al., 2024; Boy, 2024; Berretta, Tausch, Ontrup, et al., 2023; Bienefeld et al., 2024; 2023; Dubey et al., 2020; Gopinath et al., 2022; Haindl, Hoch, et al., 2022; Haindl, Buchgeher, et al., 2022; Hauptman et al., 2023; Hobbs & Li, 2024; Hong et al., 2024; Hughes et al., 2022; Kannally et al., 2023; Kleanthous, 2024; Koehl & Vangsness, 2023; Largent et al., 2018; Li, Li, et al., 2024; McNeese et al., 2021; Milella et al., 2023; Samadi et al., 2024; Schelble et al., 2024; Shukla et al., 2019; Simón et al., 2024; Stephens et al., 2023; 2021; Zhang, McNeese, et al., 2021)
		HAI Teamwork	(Jorge et al., 2023; Mallick et al., 2024; Peng et al., 2022; Schechter et al., 2023)
		HAI Team Performance	(Bansal et al., 2019a; Subramanian et al., 2024)
Relationship		Effective HAI Team	(Hemmer et al., 2022; Mozannar et al., 2023)
		HAI Team Accuracy	(Nguyen et al., 2022; Singh et al., 2023)
		HAI Robot Teaming	(Holder et al., 2021; Lematta et al., 2022)
		HAI (Military) Team	(Devitt, 2024)
		HAI (Diagnostic) Team	(Zhao et al., 2024)
		HAI Cognitive Teaming	(Vold, 2024)
		HAI Teaming Language	(Abbass et al., 2022)
		Adaptive HAI Teaming	(Malakis et al., 2023)
		HAI Teaming Intelligence	(Hoch et al., 2022)
		Collective HAI Teaming	(Zhao et al., 2022)
		HAI Teaming Approach	(Seveso et al., 2021)
		Ethical HAI Team	(Flathmann et al., 2021)
		Hybrid HAI Teaming	(Caldwell et al., 2022)
		HAI Hybrid Team	(Fuchs et al., 2024)
		HAI Partnership	(Canonica et al., 2020; Kawakami et al., 2022; Metcalfe et al., 2021; Nguyen et al., 2018; Omidvar-Tehrani et al., 2024; Waeffer & Schmid, 2020; Weisz et al., 2021; Xu, Hong, et al., 2023)
		HAI Friendship	(Brandtzaeg et al., 2022; Weijers & Munn, 2022)
		HAI Partnership Roles	(Tran, 2024)
		HAI Relationship Perception	(Tschopp & Sassenberg, 2024)
		HAI Resource Relations	(Kaarremo & Helkkula, 2024)
		HAI Companionship	(Ciriello et al., 2024)
		HAI Expert	(Virvou & Tsihrintzis, 2023)
		HAI Relations	(Al, 2023)
		Trustworthy HAI Partnership	(Ramchurn et al., 2021)
		HAI Copilot	(Li, Peng, et al., 2022)
		HAI Copilot System	(Wang, 2023)
		HAI Integration	(Collazo et al., 2024; Rago, 2022)
		HAI Co Evolution	(Ziegler & Donkers, 2024)
		HAI Roles	(Allen et al., 2022)
		HAI Loop Approach	(Bhardwaj et al., 2020)
		Adaptive, Explainable HAI Loop	(Orzikulova et al., 2024)
		Human-Aware AI	(Sreedharan, 2023)
		HCAI	(Xu & Gao, 2024)
		HAI System	(Correia & Lindley, 2022; Naikar et al., 2023; Subramonyam et al., 2022)
		HAI Ecosystem	(Contucci et al., 2022; Mulder & Meyer-Vitali, 2023)
		HAI Centric (Performance Evaluation) System	(Graça & Camarinha-Matos, 2024)
		HAI Co Orchestration	(Yang et al., 2023)
		HAI Community	(Ashktorab et al., 2023)
		HAI Ensemble	(Choudhary et al., 2025)
		HAI Entities	(Swan & Dos Santos, 2023)
		HAI Nexus	(Askarisichani et al., 2022)
		HAI Society	(Peeters et al., 2021)
		HAI Work Systems	(Klein et al., 2023)
		Hybrid HAI Orchestration	(Echeverria et al., 2023)

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Table B1. Continued.

Cluster	Subcluster	Term	Publications
Working Together	Hybrid	Proactive HAI System	(Grosinger, 2022)
		Safe, Trusted HAI System	(Akintunde et al., 2023)
		HAI Hybrid	(Allred et al., 2020; Fabri et al., 2023; Fahse & Schmitt, 2023)
	Mutual Benefit	HAI Hybrid Approach	(Paiva & Bittencourt, 2020; Zhang, Kaushik, et al., 2023)
		HAI Hybrid System	(Fuchs et al., 2023; Pereira et al., 2021)
		Hybrid HAI Tool	(Correia et al., 2023)
		HAI Symbiosis	(Bendoly et al., 2024; Ilapakurti et al., 2019; Jarrahi, 2018; Mahmud et al., 2024; Vuppapalapati et al., 2020; Zhang, Wei, et al., 2022)
	Distance	HAI Complementarity	(Holstein & Aleven, 2022; Inkpen et al., 2023; Steyvers et al., 2022; Tan et al., 2022; Yang, Zhang, et al., 2024)
		HAI Synergy	(Bao et al., 2023; Cau & Spano, 2024; Van Rooy & Vaes, 2024)
		HAI Enrichment	(Su et al., 2022)
		HAI Collab. (Bayesian) Optimization	(Arun Kumar et al., 2022)
	Comparison	HAI Alignment	(Boggust et al., 2022)
		HAI Chasm	(Kambhampati et al., 2022)
		HAI Gap	(Liu-Thompkins et al., 2022)
	Collaboration	HAI (Team Mate) Gap	(Ong et al., 2012)
		Direct HAI Comparison	(Voudouris et al., 2022)
	Collaboration	HAI Confrontation	(Zhang, Wei, et al., 2022)
		HAI Collaboration	(Agarwal, 2024; Ala-Luopa et al., 2024; Arai et al., 2023; Arias-Rosales, 2022; Ashktorab et al., 2020; Bao et al., 2021; Ben Chaaben, 2024; Biloborodova & Skarga-Bandurova, 2023; Bossen & Pine, 2023; Bousdekis et al., 2021; Braun et al., 2023; Brusilovsky, 2024; Burukina, 2020; Cabrera et al., 2023; Cabrero-Daniel et al., 2024; Cao et al., 2023; Chakravorti et al., 2023; Chang & Huang, 2021; Chen et al., 2024; Cichocki & Kuleshov, 2021; De Brito Duarte, 2023; Dellermann, Calma, et al., 2019; Dhillon et al., 2024; Erdogan et al., 2024; Eriksson et al., 2023; Erlei et al., 2024; Fan et al., 2022; Feuston & Brubaker, 2021; Figoli et al., 2022; Gamboa et al., 2022; Gao et al., 2021; Gass, 2023; Gaurav et al., 2024; Gianet et al., 2024; Göbel et al., 2022; Goel et al., 2023; Gu et al., 2024; Gupta et al., 2023; Hartikainen et al., 2024; Hassany, Ke, et al., 2024; Haupt et al., 2025; Hemmer et al., 2023; Heyman et al., 2024; Hitsuwari et al., 2023; Hohenstein et al., 2022; Holstein et al., 2023; Holter & El-Assady, 2024; Hong et al., 2021; Hou et al., 2023; Hu, Zhang, et al., 2024; Huang & Xiong, 2024; Introzzi et al., 2024; Jacobsen et al., 2020; Jaszcz et al., 2023; Jiang et al., 2021; Jiang, Liu, et al., 2023; Jones & Tanimoto, 2018; Karakose, Demirkol, Aslan, et al., 2023; Karakose, Demirkol, Yirci, et al., 2023; Khadpe et al., 2020; Kilic et al., 2023; Kim et al., 2022; 2024; Kolbjørnsrud, 2024; Kwon, Sun, et al., 2024; Lai et al., 2022; 2021; Laney & Dewan, 2024; Lauer & Wieland, 2021; Lee, Yu, et al., 2022; Li, Wang, et al., 2024; 2020; Lindner & Schulte, 2024; Linnyk & Teetz, 2023; Loo et al., 2023; Loske & Klumpp, 2021a; 2021b; Lu & Peng, 2024; Mehta et al., 2023; Meier & Glinka, 2023; Memmert & Bittner, 2024; 2022; Mlynár et al., 2024; Mohanty et al., 2024; Neuwirth & Migliorini, 2022; Okamura & Yamada, 2020a; Padovano & Cardamone, 2024; Papachristos et al., 2021; Pereira et al., 2023; Petrescu & Krishen, 2023; Prajwal et al., 2023; Puerta-Beldarrain et al., 2023; Puig et al., 2021; Qian & Wexler, 2024; Rana & Bansal, 2023; Rastogi et al., 2023; Rinott & Shaer, 2024; Sachan et al., 2024; Sadeghian et al., 2024; Saffiotti et al., 2020; Salah et al., 2023; Salikutluk et al., 2024; Sarkar, 2023; Sarkar et al., 2023; Schmidt & Biessmann, 2020; Schroder et al., 2022; Segal et al., 2022; Sharma et al., 2023; Sheno et al., 2024; Siemon, 2022; Siirtola & Röning, 2019; Söllner et al., 2023; Song et al., 2024; Sowa et al., 2021; Strobelt et al., 2022; Sun et al., 2024; Svensson & Keller, 2024; Tian, 2024; Tkouat et al., 2022; Tülübaş et al., 2023; Tuncer & Ramirez, 2022; Tutul et al., 2023; 2024; Vodrahalli, Gerstenberg, et al., 2022; Wang et al., 2019; Wang, Liu, et al., 2023; Wang, Nan, et al., 2024; Weber et al., 2023; Wellsandt et al., 2023; Westphal et al., 2023; Wiegrefe et al., 2022; Wienrich et al., 2024; Xu et al., 2020; Yan et al., 2024; Yiwon et al., 2024; You & Lowd, 2022; Yu et al., 2024; Zhang, Yu, et al., 2024; Zhao, Zhu, et al., 2023)
		HAI Collab. Approach	(Arous et al., 2020; Gomez et al., 2022; Huang, Wood, et al., 2024; Lee et al., 2021; Mesbah et al., 2023)
		Effective HAI Collaboration	(Nols et al., 2023; Reverberi et al., 2022; Vössing et al., 2022)
		Trustworthy HAI Collaboration	(Baniecki et al., 2023; Li, Karim, et al., 2023; Razmerita et al., 2022)
		HAI Collaboration Type	(Smirnov, Levashova, et al., 2023; Yue & Li, 2023)
		HAI Collab. Tool	(Kariyawasam et al., 2024; Zhang, Ning, et al., 2023)
		Process Oriented HAI Collaboration	(Heinzl et al., 2024)

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Table B1. Continued.

Cluster	Subcluster	Term	Publications
	Cooperation	Expert Knowledge Driven HAI Collaboration	(Kamboj et al., 2024)
		HAI Collaboration Patterns	(Nguyen et al., 2024)
		HAI Collab. Process	(Sankaran et al., 2022)
		Adaptive HAI Collaboration	(Shih et al., 2021)
		Constructive HAI Collaboration	(Süße et al., 2021)
		Collab. HAI	(Codella et al., 2018)
		Intuitive HAI Collab. (3D Modeling) Approach	(Cai, 2024)
		HAI Collaboration Practices	(Bogdanova, 2024)
		HAI Collab. Analysis	(Kuang, 2023)
		Critical-Reflective HAI Collaboration	(Glinka & Müller-Birn, 2023)
		HAI Collab. System	(Shi et al., 2023)
		HAI Collab. Work	(Muller et al., 2024)
		Graphical HAI Collaboration	(Hong et al., 2022)
		HAI Collab. (Navigation) System	(Gu, Yang, et al., 2023)
		HAI Cooperation	(Atkins et al., 2021; Okamura & Yamada, 2020b; Berberian et al., 2023; He et al., 2023; Li, Huang, et al., 2022; Salikutluk et al., 2023; Schelble et al., 2021; Spina et al., 2023; Zhang, Chong, et al., 2023)
	Coordination	HAI (Agent) Cooperation	(Le Guillou et al., 2023)
		Effective HAI Cooperation	(Wittmann & Morschheuser, 2022)
		Cooperative HAI Games	(Chattopadhyay et al., 2017)
		Intention Aware HAI Cooperation	(He et al., 2024)
		(Zero Shot) HAI Coordination	(Lou et al., 2023; Yan et al., 2023; Zhao, Song, et al., 2023)
	Communication	HAI Coordination	(Carroll et al., 2019; Hu & Sadigh, 2023)
		(Real Time) HAI Coordination	(Liu, Yu, et al., 2024)
		HAI Communication	(Brandtzaeg et al., 2023; Koçak et al., 2022; Pan et al., 2024)
	Co Creation	HAI Negotiation	(Sato et al., 2023)
		HAI Collab. Conversation	(Wei et al., 2022)
		HAI Co Creation	(Du et al., 2024; Fu & Zhou, 2020; Gmeiner et al., 2024; Suh et al., 2024; Hassany, Ke, Brusilovsky, Arun, et al., 2024; Hofmann & Preiß, 2023; Huang et al., 2020; Lyu et al., 2022; Ning et al., 2024; Rezwana & Maher, 2023a; Turchi et al., 2023; Wang, Ning, et al., 2024; Wang, Nan, et al., 2024; Wu, Kim, et al., 2022; Zhong & Zheng, 2023; Zhu et al., 2024)
	Task Distribution	HAI Co Creativity	(Kim, Maher, et al., 2021; Moruzzi & Margarido, 2024; Rezwana & Maher, 2023c; Karimi et al., 2020; Wan et al., 2024)
		HAI Co Creative System	(Buschek et al., 2021; Rezwana & Maher, 2023b; Rezwana & Maher, 2021)
		HAI Knowledge Co-Construction	(Robertson et al., 2024)
		HAI System Co Creativity	(Serbanescu, 2024)
		HAI Text Co Creation	(Ding et al., 2023)
		(Real-Time) HAI Co Creation	(Zheng, 2023)
		HAI Co Creation Model	(Wu et al., 2021)
		HAI Co Creative Songwriting	(Micchi et al., 2021)
		HAI Co Creative (Design) Ideation	(Rezwana et al., 2021)
		HAI (Music) Co Creation	(Zhang, Xia, et al., 2021)
		Generative HAI Co Creation	(Chung et al., 2022)
		Creative HAI (Image) Co Creation	(Fan et al., 2024)
		HAI Co Creation Practice	(Yu et al., 2022)
		HAI Co Creative Drawing	(Lawton et al., 2023)
		HAI Delegation	(Adam et al., 2024; Grisold & Schneider, 2023)
		HAI Crowd Task Assignment	(Kanda et al., 2022; Kobayashi et al., 2021)
		Integrated HAI Forecasting	(Li, Yin, et al., 2024)
		Hybrid HAI Forecasting	(Li & Lafond, 2023)
	Interaction	HAI Interaction	(Abedin et al., 2022; Ahn et al., 2024; Alon-Barkat & Busuioc, 2023; Amershi et al., 2019; Anderson et al., 2024; Ashktorab et al., 2021; Bach et al., 2024; Bernardo & Seva, 2024; Bondi et al., 2022; Bozdag, 2023; Calisto et al., 2022; Chen & Schmidt, 2024; Cheng et al., 2022; Cotino Arbelo et al., 2023; Crompton, 2021; Correia et al., 2021; Ding, 2024; Dynel, 2023; El-Assady & Moruzzi, 2022; Giudici et al., 2024; Gammelgård-Larsen et al., 2024; Guingrich & Graziano, 2024; Guttman et al., 2021; Gurney et al., 2023; He & Jazizadeh, 2024; Heyder et al., 2023; Hois et al., 2019; Hu, 2024; Hu, Liu, et al., 2024; Jang & Nam, 2022; Jiang et al., 2022; Jiang, Sun, et al., 2024; Jiang, Karran, et al., 2023; Jin & Youn, 2023; Judkins et al., 2024; Kiyemba et al., 2024; Kim et al., 2023; Krakowski et al., 2024; Krueger & Roberts, 2024; Kwon, Yoo, et al., 2024; La Sala et al., 2024; Lee, Hong, et al., 2023; Lee, Lee, et al., 2023; Legaspi et al., 2024; Li, Vorvoreanu, et al., 2023; Li & Lu, 2024; Liu, 2021; Liu & Siau, 2023; Lu et al., 2023; Ma & Huo, 2024; Maadi et al., 2021; Maeda & Quan-Haase, 2024; Maletzki et al., 2024; Meske & Bunde, 2020; Mucha et al., 2021; Muijlwijk et al., 2024; Navidi & Landry, 2021; Park et al., 2021; Pham et al., 2022; Raees et al.,

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Table B1. Continued.

Cluster	Subcluster	Term	Publications
			2024; Rajagopal & Vedamanickam, 2019; Roeder et al., 2023; Schoenherr & Thomson, 2024; Shergadwala & El-Nasr, 2021; Shin et al., 2019; Snotos et al., 2024; Sqalli et al., 2021; Sreedharan, 2023; Sreedharan et al., 2021; Süße et al., 2023; Sundar, 2020; Tenhundfeld, 2023; Tchemeube et al., 2023; Thieme et al., 2020; Tsiakas & Murray-Rust, 2024; Ueno et al., 2022; van Berkel et al., 2021; Vassilakopoulou et al., 2023; Veitch & Alsos, 2022; Villareale et al., 2023; Vorm, 2020; Vodrahalli, Daneshjou, et al., 2022; Wallinheimo et al., 2023; Wang et al., 2021; Wang, Liu, et al., 2023; Wienrich & Latoschik, 2021; Wu, Kim, et al., 2022; Xu & Ge, 2024; Yang et al., 2020; Yang, Xie, et al., 2024; Yao et al., 2024; Kang & Lou, 2022; Liao & Sundar, 2021; Hwang & Won, 2022)
		HAI Dynamics	(Khushk et al., 2024)
		HAI Metaphorical Interplay	(Correia, 2024)
		HAI Interaction Dashboard	(Kongmanee et al., 2024)
		Tangible HAI Interaction	(Adan & Houben, 2023)
		Multimodal HAI Interaction	(Scotte & De Silva, 2023)
		HAI Robot Interaction	(Feng & Wang, 2023)
		HAI Information Interaction	(Pawlick-Potts, 2022)
		Dynamic HAI Interplay	(Meyer & Voigt, 2022)
		HAI Interactive Approach	(Kou et al., 2022)
		HAI Interaction Dynamics	(Kim & Trehwhitt, 2022)
		Purposeful HAI Interaction	(Hinsen et al., 2022)
		HAI Interface	(Holzinger & Müller, 2021)
		Explainable HAI Interaction	(Guerdan et al., 2021)
		Voice-Based HAI Interaction	(Shin et al., 2021)
		HAI Interaction Patterns	(Grabe et al., 2022)
		HAI Attention	(Zhang et al., 2020)
		HAI Hybrid Adaptivity	(Holstein et al., 2020)
		HAI Social Interaction	(Mou & Xu, 2017)
		Actionable HAI Interaction	(Bhattacharya, 2024)
		Beginner Friendly HAI Platform	(Overney et al., 2024)
		HAI Interaction Model	(Hussain et al., 2024)
		HAI Physical Interface	(EL-Zanfaly et al., 2022)
		Transparent, Controllable HAI Interaction	(Wu, Terry, et al., 2022)
		Conversational HAI Interaction	(Zheng et al., 2022)
		HAI Interaction Loop	(Ou et al., 2022)
		HAI Interaction Design Space	(Zhang, Liu, et al., 2021)
		Bidirectional HAI Interaction	(Yasser & Abu-Elkhiar, 2022)
		Combined HAI Personalization	(Chine et al., 2022)
	Experience and Trust	HAI Trust	(Bui et al., 2023; Li, Wu, et al., 2024; Lou & Wei, 2023; Schwalb et al., 2022; Wang & Ding, 2024; Zerick et al., 2024)
		HAI Experience	(Inkpen, 2024; Sergeyuk et al., 2024; Weekes & Eskridge, 2022)
		HAI Interaction Satisfaction	(Xie et al., 2023)
		HAI Performance	(Hoffman et al., 2023)
		HAI Trust Dynamics	(Gerlich, 2024)
		HAI Trust Factors	(Pham et al., 2022)
		Hybrid HAI Performance	(Lemus et al., 2023)
	Work and Tasks	HAI Work	(Berretta, Tausch, Peifer, et al., 2023; Hüllmann et al., 2023; Ruissalo, 2024)
		HAI Collab. Task	(Dodeja et al., 2024; Weerawardhana et al., 2024)
		HAI Collaboration Task	(Sharma et al., 2024; Xu, Lien, et al., 2023)
		HAI Coworking	(Huang, Chen, et al., 2024)
		HAI Crowdsourcing	(Tamura et al., 2024)
		Effective HAI Work Design	(Jain et al., 2023)
		HAI Collab. (Sub-Goal) Optimization	(Ma, Vo, et al., 2023)
		HAI Complex Task Planning	(Nikookar, 2023)
		HAI Joint Task Performance	(Constantinides et al., 2024)
Applications	Decision Making	HAI Decision Making	(Salimzadeh et al., 2024; Jakubik et al., 2023; Morrison et al., 2024; Schoeffer et al., 2024; Goyal et al., 2024; Chen, Wu, et al., 2023; Prabhudesai et al., 2023; Salimzadeh et al., 2023; Lai et al., 2023; Schemmer et al., 2022; Liu et al., 2021)
		HAI Collab. Decision Making	(Wang, Yuan, et al., 2024; Mentzas et al., 2021; Puranam, 2021; Cai et al., 2019)
		Effective HAI Decision Making	(Schemmer et al., 2023; Bućinca 2024)
		Collab. HAI Decision Making System	(Oksana et al., 2022; Dolgikh & Mulesa, 2021)
		HAI Collab. Decision Support System	(Smirnov, Ponomarev, et al., 2023)
		HAI Visual Decision Making	(Morrison et al., 2023)
		HAI Collab. (Clinical) Decision Making	(Lee & Chew, 2023)
		HAI Collab. (Clinical) Decision Support System	(Lee, Siewiorek, et al., 2022)
	Learning	HAI Co Learning	(Schoonderwoerd et al., 2022; van den Bosch et al., 2019)
		Hybrid HAI Regulation	(Molenaar, 2022a)
		Hybrid HAI Tutoring	(Thomas et al., 2024)

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**Table B2.** Key publications with citation counts within the 99th percentile, average citation counts per year are shown in brackets.

Publication	Authors	Year	Cites (Avg.)	Cluster	Keywords and Description
(Jarrahi 2018)	Jarrahi	2018	2,027 (290)	Connection	Artificial intelligence; Organizational decision making; Human-machine symbiosis; Human augmentation; Analytical and intuitive decision making This paper attempts to mitigate fears of human replacement and loss of employment with AI emergence in business contexts. It highlights the opportunity for enhancement rather than replacement of human capabilities due to the human-AI complementarity in complex decision making processes.
(Amershi et al., 2019)	Amershi et al.	2019	1,563 (261)	Working Together	Human-AI interaction; AI-infused systems; design guidelines A set of 18 evaluated guidelines for human-AI interaction is proposed to account for the rapid advances of AI systems and the adoption of human-AI systems, overgrowing the research in past decades. Guidelines are categorized by the time of occurrence ranging from before to during the interaction, error handling and over time adaptability.
(Yang et al., 2020)	Yang et al.	2020	527 (105)	Working Together	User experience, artificial intelligence, sketching, prototyping The design of human-AI interaction proves to be more challenging to HCI researchers and practitioners than regular prototyping and sketching of complex systems. This paper shifts away from focusing on the technical complexity of AI systems and rather identifies properties such as uncertainty and adaptability of AI systems as challenges in interaction design.
(Cai et al., 2019)	Cai et al.	2019	462 (77)	Applications	Human-AI interaction; machine learning; clinical health A qualitative lab study shows that explanations in human-AI collaboration are not enough for human medical experts. Comprehensive information about the general function, expectable capabilities and limitations helps in finding a compatible partner that can be relied on for collaborative decision making.
(Bansal et al., 2019a)	Bansal et al.	2019	456 (76)	Connection	no keywords Human-AI teams can exceed individual performance. To be able to utilize the complementary capabilities, however, it is essential that the two parties can estimate each other's capabilities and how to complement them. This study focuses on the impact of human mental models of AI systems in AI-advised decision making.
(Sundar 2020)	Sundar	2020	444 (89)	Working Together	Source Interactivity; Machine Heuristic; Artificial Intelligence (AI); Algorithms; User Experience; Human-AI Interaction (HAI); Theory of Interactive Media Effects (TIME) Research in computer-mediated communication (CMC) no longer focuses solely on supporting human communication but has shifted towards humans actually communicating with the technology itself, too. The different degrees of agency and interactivity shape the human-AI collaboration potential and the authors expect a conversion from HCI to HAI (Human-AI Interaction) research.
(Carroll et al., 2019)	Carroll et al.	2019	397 (66)	Working Together	no keywords In human-AI coordination there is a gap in agent's capability to adapt to agents or to human partners. To reach complementarity rather than individual peak performance, agents need to encounter humans during the training process, which is missing in the common training strategies.