Disentangling Human-AI Hybrids –

Conceptualizing the Interworking of Humans and AI-Enabled Systems

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Appendix 1: Literature Review and Human-AI Hybrids Sample Compilation

To capture both existing research and real-world applications of human-AI hybrids as the basis for developing our taxonomy, we base our research on a comprehensive review of both. We started this study by searching the existing literature on the collaboration of human agents and AI-enabled systems for relevant, high-quality articles following the guidelines of Webster and Watson (2002) and vom Brocke et al. (2015). In doings so, we applied a twofold search strategy to account for academic relevance and real-world applications.

We began by searching the scientific databases AIS electronic library, ACM digital library, EBSCOhost BusinessSource Premier, and ScienceDirect in an initial explorative literature review to identify key publications and relevant related search terms. Seeing that the basic concepts underlying human-AI hybrids have been studied in various disciplines and research streams (e.g., IS, HCI, HRI, HMI, engineering, and management), we decided to cover the three major elements with our search string. First, we included the "human" element in human-AI hybrids. Our second concern was with "artificial intelligence", including the short form "AI", which is used to account for relevant terminological variations related to the context of systems or applications, such as "AI-based", "AI-enhanced", and "AI-enabled". Our third concern was with "hybrid" and "collaboration" since both terms are often used to denote the interworking of human agents and AI-enabled systems. We applied this composite search string – ("Human") AND ("Artificial Intelligence" OR "AI") AND ("Hybrid" OR "Collaboration") – to the aforementioned databases. Searching titles and abstracts resulted in 595 relevant publications, all of which we screened for exclusion. We, first, discarded publications that while containing our search string were unrelated to the field of human-AI hybrids. We then performed a detailed review of the remaining articles to exclude all those with no information on relevant characteristics of human-AI hybrids. After screening titles, abstracts, and full texts, we obtained a sample of 32 articles, whereupon we applied a forward-backward search and arrived at a final number of 49 relevant articles. These articles cover a broad range of different perspectives on the subject matter. Thus, we found that we could build our research on a broad knowledge base that encompasses current debates, theories, and taxonomies in the realm of human-AI hybrids.

Subsequently, we put together a sample of human-AI hybrids. To ensure the relevance of this sample, we added a fourth block to our search string related to practical applications: “use case”, “case study”, “pilot project”, “application”, and “prototype”. In this second round of literature review, we also looked at an additional database, namely the IEEE Xplore digital library, as it contains more case studies and application-oriented publications. We refrained from including this database in the initial review because papers in the library are usually less focused on foundational studies but more on the results of application. In this second literature review, our initial search of titles and abstracts resulted in 390 publications of interest. Upon screening the titles, abstracts, and keywords of those publications, we excluded those unrelated to human-AI hybrids, then read the full text of each remaining article, and dismissed those that did not feature at least one well-described human-AI hybrid use case. Based on this, we were able to reduce the number of publications to 21. Again, we applied a forward-backward search to ensure that we cover relevant publications related to our topic. Furthermore, we searched several search engines (i.e., Google Scholar, Semantic Scholar, and Scopus) for relevant practice-oriented articles and books. Ultimately, we were able to identify 29 publications that provided a total of 95 use cases and a sample of 101 human-AI hybrids (see Table A. 1).

Table A. 1: Sample of human-AI use cases and hybrids

References	**Use cases**	**Human-AI hybrids**
Agrawal et al. (2018)	Chisel Legal Document Processing	Human legal employee + AI-enabled document processing system
	Grammarly Spelling Correction	Human editor + AI-enabled spelling correction system
	Atomwise Drug Prediction	Human researcher + AI-enabled drug prediction system
Ansari et al. (2019)	Prescriptive Maintenance for CPP	Human maintenance manager + AI-enabled maintenance analysis system
		Human knowledge engineer + AI-enabled maintenance analysis system
Berger et al. (2021)	Call Center Estimation	Forecaster + AI-enabled analysis system
Daugherty and Wilson (2018)	Rio Tinto	Human machine controllers + AI-enabled mining machinery system)
		Data analyst + AI-enabled mining machinery system
	Fanuc	Human worker + AI-enabled robotic support system
	Hitachi	Human worker + AI-enabled big data analysis system
	Inertia Switch	Human agent + AI-enabled system
	Fraunhofer Institute of Material Flow and Logistics	Assembly worker + AI-enabled assembly line control system

		Process engineer + AI-enabled assembly line control system
	GE Reimagined Maintenance	Human agent + AI-enabled maintenance system
	GE Reimagined product development	Human agent + AI-enabled sensor system
	Kiva Robots	Human agent + AI-enabled robots
	Symbotic robots	System operator + AI-enabled packing robots
	Procter & Gamble	Human agent + AI-enabled supply chain system
	Accenture Precision Agriculture Sevice	Farmer + AI-enabled agriculture system
	Anti-Money-Laundering Detection	Human investigator + AI-enabled detection system
	Virgin Trains inSTREAM	Human reviewer + AI-enabled review system
	HireVue Unilever's process for hiring	Human investigator + AI-enabled detection system
	Gigster Code Assistant	Human developer + AI-enabled code assistant system
	SEB Amelia Customer Service	Human service agent + AI-enabled interaction system
		Human supervisor + AI-enabled interaction system
	Quid Natural-Language Processing	Human investor + AI-enabled NLP system
	GNS REFS	Human researcher + AI-enabled reverse engineering system
	Nike Sprinting Shoe	Human designer + AI-enabled 3D design system
	SigOpt General Optimization	Human researcher + AI-enabled Prompting system
	Numerate	Human researcher + AI-enabled identification system
	Coca-Cola Einstein	Human retail employee + AI-enabled cooler managing system
	Philips Hue smart lighting	Human replacement service worker + AI-enabled detection system
	Ralph Lauren Smart Mirror	Human associate + AI-enabled smart mirror system
	Percolata Staffing Scheduling	Staff managers + AI-enabled staff schedule system
	6sense mailing service	Human salesperson + AI-enabled marketing system
	Yahoo language-processing system	Human linguistic trainer + AI-enabled NLP system
	BlackRock quantamental funds	Human investor + AI-enabled detection system
	ZestFinance Loan Application	Human employee + AI-enabled loan application system
	Autodesk	Human designer + AI-enabled design system
	Phillips Illumeo Radiology	Human investigator + AI-enabled detection system
Davenport et al. (2020)	Online retailing AI (e.g., Birchbox)	Human retail agent + AI-enabled prediction system
	Fashion-related AI (e.g., Stitch Fix)	Human stylist + AI-enabled product curation system
	Sales AI (e.g. Conversica)	Human sales agent + AI-enabled chat bot system
	Customer screening AI (e.g. Kanetix)	Human insurance agent + AI-enabled prediction system
	Business process AI (e.g., Bank of Montreal)	Human service agent + AI-enabled analysis system

	Retail store AI (e.g., Café X)	Human sales associate + AI-enabled sales assistant system
	Security AI (e.g., Knightscope's K5)	Human security personnel + AI-enabled sensor system)
Davenport and Kirby (2015)	Gongos Consumer Insights	Human marketing researcher + AI-enabled marketing analysis system
	Berg Drug Discovery	Human chemist researcher + AI-enabled biochemist analysis system
Davenport (2018)	Vanguard Personal Advisor Services	Human advisor + AI-enabled investment advice system
	Bank of New Zealand Intel Saffron	Human investigator + AI-enabled transaction investigation system
	Lola Travel Agent	Human travel agent + AI-enabled travel recommendation system
	Danske Bank Denmark	Human employee + AI-enabled online behavior analysis system
	Digital Reasoning Employee Monitor	Human investigator + AI-enabled investigation system
	Kone Technician Dispatching System	Human technician + AI-enabled dispatching system
	Everstring Customer Insights	Human salesperson + AI-enabled customer insight system
Doltsinis et al. (2018)	Hybrid Ramp-up Process	Human operator + AI-enabled ramp-up system
Green and Chen (2019)	Risk Assessment	Human judges + AI-enabled risk assessment system
Grønsund and Aanestad (2020)	Configuration upon the introduction of the algorithm: auditing and altering conducted by the data scientist	Human data scientist + AI-enabled processing system
	Reconfiguration involving domain experts in auditing and data scientist in altering of the algorithm	Human data scientist + AI-enabled processing system
		Human domain experts + AI-enabled processing system
	Reconfiguration repurposing the role of the researcher and enrolling data analyst to the auditing work	Human researcher + AI-enabled processing system
		Human data analyst + AI-enabled processing system
Heer (2019)	Collaborative Interface for Data Wrangling	Human data analyst + AI-enabled data wrangling system
	Collaborative Interface for Exploratory Analysis	Human data analyst + AI-enabled analysis system
	Collaborative Interface for Natural Language Translation	Human data analyst + AI-enabled NLP system
Iansiti and Lakhani (2020)	Walmart AI-enabled Supermarket Stores	Human salesperson + AI-enabled customer analysis system
	Alipay Credit Service	Human data analyst + AI-enabled credit system
	Ocado Automated Warehouse	Human picking employee + AI-enabled automated warehouse system
	Fidelity Investment	Human advisor + AI-enabled investment advice system
Jussupow et al. (2021)	Diagnostics	Human physician + AI-enabled medical diagnosis system
Kahn et al. (2020)	Call Center Customer Service	Human call center agent + AI-enabled call center system
Klumpp (2018)	Automated driving	Human truck driver + AI-enabled driving systems
Lai et al. (2020)	Smart augmented instruction system for mechanical assembly	Human worker + AI-enabled smart assist system
Liew (2018)	Detection and prediction automation	Human radiologist + AI-enabled radiologic analysis system
	Intelligence augmentation	Human radiologist + AI-enabled radiologic analysis system
	Radiological decision support systems	Human radiologist + AI-enabled decision support system

McAfee and Brynjolfsson (2017)	Civis Analytics	Human data analyst + AI-enabled scoring system
	Google Hiring Process	Human HR employee+ AI-enabled scoring system
	Fukoku Mutual Life	Human data analyst + AI-enabled scoring system
	IBM Watson Kinases Detection	Human researcher + AI-enabled kinases detection system
	Shanghai Tower	Human architect + AI-enabled building design system
Mirbabaie et al. (2021)	Virtual Assistant	Human agent + Virtual Assistant
Paschen et al. (2020)	Prospecting	Human marketing agent + AI-enabled prospecting system
	Pre-approach and Approach	Human marketing agent + AI-enabled marketing system
	Presentation	Human marketing agent + AI-enabled marketing system
	Overcoming objections and Closing	Human marketing agent + AI-enabled marketing system
	Follow-up	Human marketing agent + AI-enabled marketing system)
Schmitt et al. (2020)	Predictive model-based quality inspection	Human employee + AI-enabled quality prediction system
Shin et al. (2021)	AI-assistance for predictive maintenance	Human inspector + AI-enabled predictive maintenance system
Sowa et al. (2021)	Chat bot for decision making in marketing	Human decision maker + AI-enabled virtual assistant
Syam and Sharma (2018)	Finovate Robo-Adivsors	Human advisor + AI-enabled robo advisor system
	Harley-Davidson Lead Generation	Human salesperson + AI-enabled marketing analysis system
	Gainsight Sales Management	Human salesperson + AI-enabled sales analysis system
	LG Smartphone Service	Human service personnel + AI-enabled service system
Tsang et al. (2018)	Cold Supply Risk Management System	Human logistics worker+ AI-enabled risk management system
van Dun et al. (2023)	Consideration of domain knowledge by incorporating a human in the loop	Human domain expert + AI-enabled ProcessGAN system
Yin et al. (2013)	Collaborative Interface for Aero-Engine Pipe Routing	Human designer + AI-enabled design system
Zhang et al. (2021)	Goods Storing	Human worker + AI-enabled storing system
	Order Picking	Human worker + AI-enabled picking system
	Order Packing	Human worker+ AI-enabled packing system

Appendix 2: Taxonomy Development Process

In the following, we provide details on our four iterations of taxonomy development following the steps displayed in Fig. A. 1.

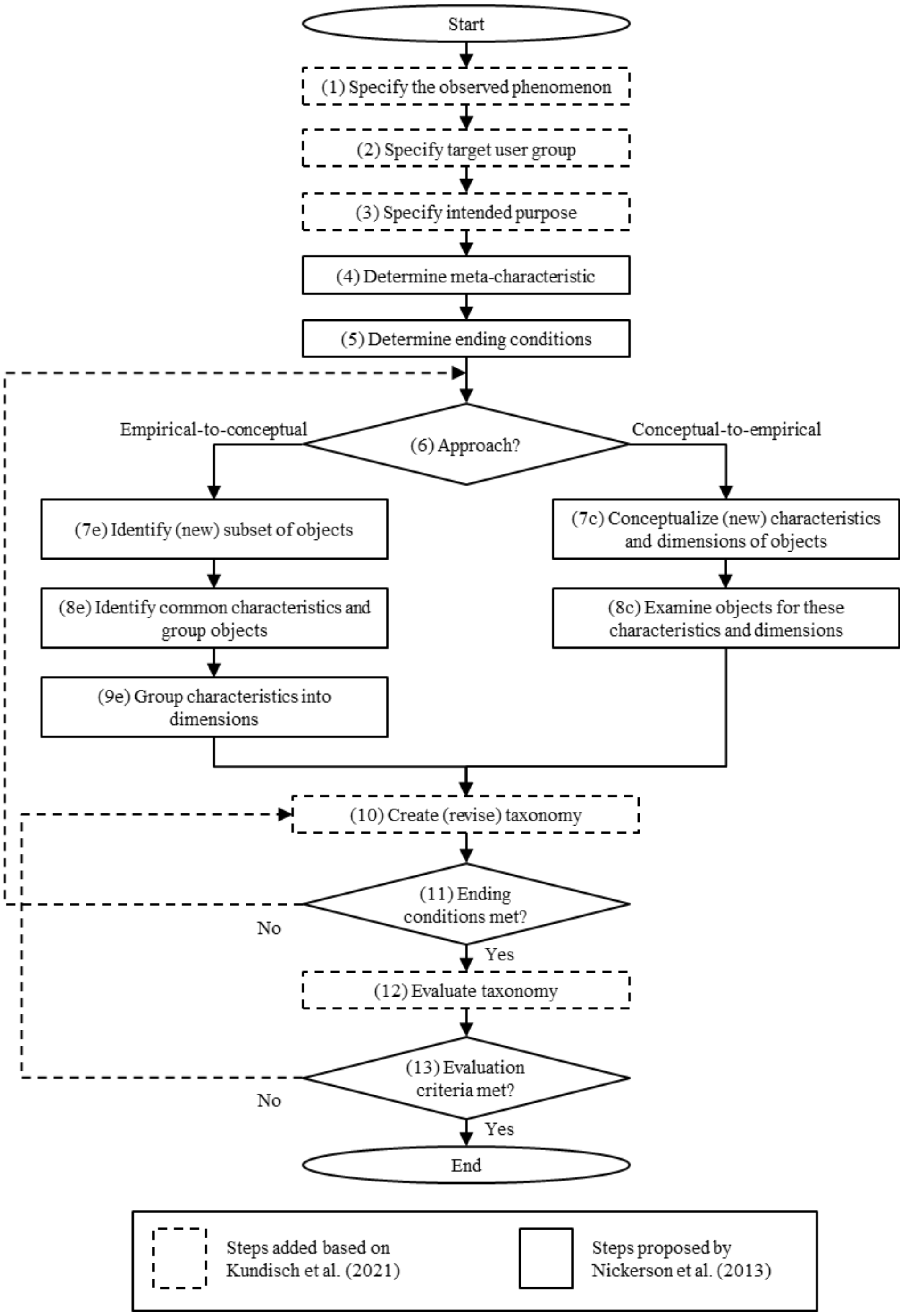

Figure A. 1: Adopted taxonomy development method based on Kundisch et al. (2022)

Step 1: We specified the observed phenomenon as human-AI hybrids. More specifically, upon reviewing the discussion on human agents and AI-enabled systems, we observed the dominantly in binary terms conducted discussion of human agents and AI-enabled systems as rivals fighting for the other's jobs in the context of human-AI hybrids.

Step 2: We defined our target user group to IS researchers and researchers from other fields related to the topic of human-AI hybrids (e.g., HCI, (cognitive) psychology) along with high- and mid-level decision-makers concerned with the use and integration of AI. We chose this target user group because, agreeing with Sarker et al. (2019), we feel a strong obligation to encourage a more nuanced discussion about the integration of AI in the future of work. Most likely, however, it will be organizations and their respective decision-makers who will drive the symbiotic interworking of humans and AI within those organizations, which is why we include them in the compass of this study, the aim being to facilitate a better understanding and thus stimulate the creation of new human-AI hybrids.

Step 3: We specified the purpose of our taxonomy to understanding what characterizes the symbiotic interworking of human agents and AI-enabled systems when they augment one another.

Step 4: We defined "the relevant properties of the collaborative interworking of human agents and AI-enabled systems" to be the meta-characteristic for developing our taxonomy.

Step 5: We defined our objective ending conditions: at least one object is classified to possess every characteristic of every dimension, no new dimensions or characteristics were added in the last iteration, no dimensions or characteristics were merged nor split in the last iteration, every dimension is unique, and every characteristic is unique within its dimension.

We also defined the subjective ending conditions: concise, robust, comprehensive, extendible, and explanatory. We chose these ending conditions because they ensured sufficient comprehensiveness as well as manageability in every iteration.

Iteration 1

Step 6: Since we identified a diverse existing body of knowledge on human-AI collaboration, we decided to use it as starting point for our taxonomy development process. That is, we applied a conceptual-to-empirical approach in our first iteration.

Step 7c: In Iteration 1, we first analyzed the existing body of knowledge in the form of scientific contributions and studies based on an extensive literature review on the state-of-the-art of human-AI hybrids. During this process, we also found that the concept behind human-AI hybrids is researched by various disciplines and research streams (e.g., information systems, human-computer interaction, human-robot interaction, human-machine interaction, engineering, and management.). Consequently, our literature review provided us with a broad foundation concerning current debates and theories but also existing taxonomies.

Subsequently, three of the authors discussed the relevant articles from our literature review and their contributions to the understanding of human-AI hybrids in an iterative process. That is, going through our sample of existing literature on human-AI hybrids, we added, merged, and, if necessary, removed identified characteristics and dimensions into an initial version of our taxonomy. Driven by the purpose of our taxonomy (understanding the characteristics of the collaborative interworking of human agents and AI-enabled systems to augment and enhance each other), we aimed to obtain a comprehensive picture of the integral parts of human-AI hybrids. Drawing from weak sociomateriality and its five constituting dimensions (materiality, inseparability, relationality, performativity, and practice) as justificatory knowledge, enabled us to leverage insights that go beyond a mere accumulation of characteristics and dimensions. Focusing on sociomaterial practices in human-AI hybrids, for example, helped us understand that the interaction from the human to the AI and vice versa results in a higher-level entanglement of both. As a result, we identified both the interaction from the human to the AI and the interaction from the AI to the human as relevant for an explanation of the collaborative interworking in human-AI hybrids and, therefore, implemented them in our taxonomy.

Additionally, weak sociomateriality helped us to identify *human* and *AI* as separate entities of human-AI hybrid assemblages (Barad 2007), and sociomaterial practices as a result of their entangled interworking (Leonardi 2013). As a result, we implemented *human*, *AI*, and *socialmaterial practices (initially task)* as sociomaterial entites into our taxonomy to further structure our relevant dimensions. In our first iteration, we also established *structure* as a fourth entity, but later refrained from using it due to a missing fit to the purpose of our taxonomy.

Step 8c: Since we already identified a minor amount of human-AI hybrids in our initial literature review, we were able to validate the characteristics and dimensions identified in iteration 1 by evaluating their applicability on those human-AI hybrids (Varshney 2014). This also allowed us to confirm that all entities, dimensions, and characteristics were in line with our meta-characteristic.

Step 10: After grouping the relevant dimensions and characteristics, we created a first version of our taxonomy T1 comprising 4 entities, 11 dimensions and 40 characteristics. Following the taxonomy notation of Nickerson et al. (2013), we describe a taxonomy T as a set of n entities E_i $(i = 1, \ldots, n)$ with m dimensions D_{ij} $(j = 1, \ldots, m)$ each consisting of o_{ij} $(o_{ij} \geq 2)$ characteristics C_{ijk} $\left(k = 1, \ldots, o_{ij}\right)$:

$$T = \left\{E_i, i = 1, \ldots, n \middle| E_i = \left\{D_{ij}, j = 1, \ldots, m \middle| D_{ij} = \left\{C_{ijk}, k = 1, \ldots, o_{ij}; o_{ij} \geq 2\right\}\right\}\right\}$$

T1 = {

Human {Core cognitive functions {Empathy, Judgement, Creating, Problem-solving, Decision-making}, Actions {Improve, Supplement, Facilitate}, Roles {Trainer, Explainer, Sustainer}},

AI {Core cognitive functions {Reasoning, Predicting, Planning, Decision-making, Organizing, Communicating, Creating}, Actions {Guide, Improve, Replace}, Roles {Amplifier, Interactor, Embodier}},

Task {Human-AI relationship {Competition, Interworking, Augmentation}, Process adaptation {None, Transformation}, Learning {AI learns, Human learns, Both learn}},

Structure {Resources {Data, Algorithms, Robots, Humans, IT infrastructure}, Requirements {Task specification, Performance metrics, Training experience}}

}.

Step 11: The taxonomy resulting from iteration 1 neither met all our subjective nor our objective ending conditions. Notably, we were not able to classify at least one object under every characteristic of every dimension. Moreover, it was apparent that the first version of our taxonomy was neither comprehensive nor concise. Hence, we decided to perform another iteration.

Iteration 2

Step 6: To enrich our perspective on human-AI hybrids with insights from other researchers and to account for additional relevant publications not identified in our initial literature review, we decided to perform another conceptual-to-empirical iteration based on a panel discussion with other IS researchers.

Step 7c: In iteration 2, we thus discussed the first version of our taxonomy in a large panel (30+ participants) that included IS researchers with a broad range of research foci (e.g., AI, innovation management, Internet of Things (IoT), and strategic IT management). This heterogeneous panel enabled an interdisciplinary discussion of the results of our taxonomy development process. This discussion led to the discovery of additional research streams and topics of interest (e.g., human-robot interaction, a sociological perspective on human-AI hybrids, and potential focus areas of human agents and AI-enabled systems in human-AI hybrids).

After performing a supplementary literature review and analysis based on the input from the discussion, we adjusted our taxonomy. That is, we refined some of our dimensions (e.g., we added *automation* and removed *interworking* from the *paradigm* dimension) and added additional relevant characteristics (e.g., we added a *human and AI learn* characteristic to the *learning* dimension). We also identified additional relevant dimensions, such as the *form of interworking* and *time*. Moreover, we decided to eliminate the *structure* entity because it was not seen as a matter of the concrete collaboration of human agents and AI-enabled systems (i.e., sociomaterial practices), but rather of the environment in which a human-AI hybrid is established.

Step 8c: Again, we validated the resulting characteristics and dimensions with an application of our taxonomy on some of the human-AI hybrids we identified during our literature review. We also ensured that new characteristics were in line with our meta-characteristic.

Step 10:

At the end of iteration 2, our taxonomy T2 comprised 3 entities, 11 dimensions and 43 characteristics.

T2 = {

> *Human* {Core cognitive functions {Empathy, Judgement, Creating, Problem-solving, Decision-making}, Actions {Improve, Supplement, Facilitate}, Roles {Trainer, Explainer, Sustainer}},
>
> *AI* {Core cognitive functions {Reasoning, Predicting, Planning, Decision-making, Organizing, Communicating, Creating}, Actions {Guide, Improve, Replace}, Roles {Amplifier, Interactor, Embodier}},
>
> *Task* {Paradigm {Automation, Augmentation, Competition}, Process adaptation {None, Transformation}, Form of interworking {Parallel, Sequential, Mixed}, Time {Synchronous, Asynchronous, Mixed}, Learning {AI learns, Human learns, Human and AI learn, Co-evolution}}

}.

Step 11: The taxonomy resulting from iteration 2 neither did meet all our subjective nor our objective ending conditions. Analyzing the validation results, we concluded that our taxonomy was concise, extendible, and explanatory. However, the taxonomy was not yet comprehensive because not all human-AI hybrids from the sample could be classified. Moreover, we found that the robustness of our taxonomy could still be improved. Therefore, we decided to perform a third iteration.

Iteration 3

Step 6: To account for the comprehensiveness and robustness of our taxonomy, we decided to analyze and classify existing human-AI hybrids by applying an empirical-to-conceptual approach.

Step 7e: Therefore, in iteration 3, we resorted to our compiled sample of 101 human-AI hybrids. Choosing a diverse subset of hybrids from this sample, three of the co-authors iteratively discussed every hybrid and its classification with our taxonomy. We focused on identifying common attributes as well as differentiators in our hybrids and tested the entities, dimensions, and characteristics of our taxonomy accordingly.

Step 8e: During the analysis of the hybrid subset, we found that AI-enabled systems can also supplement human agents by complementing their cognitive functions to perform tasks collaboratively. We also found cases were the human agent audits the results of an AI-enabled system to ensure a correct output. Moreover, human agents in our human-AI hybrids also assumed the role of a cognitive as well as a physical co-worker based on their specific contribution to the completion of a task.

All identified characteristics were in line with our meta-characteristic as they represent relevant properties of the collaborative interworking between human agents and AI-enabled systems.

Step 9e: As AI-enabled systems *supplementing* human agents clearly is a relevant action, we integrated it into the *action* dimension of the *AI* entity. Additionally, we renamed this dimension to *interplay AI2H* to better reflect the fact that it is an action directed towards the human. Correspondingly, we also renamed the *action* dimension of the *human* entity to *interplay H2AI*. Moreover, we integrated *audit* as an additional characteristics of the *interplay H2AI* dimension. We added clarification to the respective *roles* dimensions of the entities *human* and *AI* by renaming them to *roles of AI* and *roles of humans*. As they fit the context of roles, we also integrated *physical co-worker* and *cognitive co-worker* in the *roles* dimension of the *human* entity.

Step 10: At the end of iteration 3, our taxonomy T3 comprised 3 entities, 11 dimensions and 41 characteristics.

T3 = {

> *Human* {Human CF {Empathizing, Judging, Creating, Problem-solving, Decision-making}, Interplay H2AI {Improve, Supplement, Facilitate, Audit}, Roles of humans {Trainer, Explainer, Sustainer, Cognitive co-worker, Physical co-worker}},
>
> *AI* {AI CF {Reasoning, Predicting, Planning, Decision-making, Organizing, Communicating, Creating}, Interplay AI2H {Guide, Supplement, Correct, Replace}, Roles of AI {Amplifier, Interactor, Embodier}},

Task {Paradigm {Automation, Augmentation, Competition}, Process adaptation {None, Transformation}, Form of interworking {Parallel, Sequential}, Time {Synchronous, Asynchronous}, Learning {AI learns, Human learns, Human and AI learn, Co-evolution}}

}.

Step 11: The classification of human-AI hybrids resulted in a few additions of characteristics as well as some minor changes to the wording of dimensions. Therefore, we concluded that our taxonomy was now more comprehensive and robust than before. However, as we performed modifications to our taxonomy, we still did not meet our objective ending conditions. Hence, we decided to perform an additional fourth iteration.

Iteration 4

Step 6: To cross-check the validity of the results from the analysis and discussion of human-AI hybrids in the previous iteration as well as the robustness and comprehensiveness of our taxonomy, we again adopted an empirical-to-conceptual approach based on the classification of human-AI hybrids.

Step 7e: To confirm the validity and the applicability of the latest version of our taxonomy, we randomly selected additional human-AI hybrids from our sample and discussed and classified them.

Step 8e: These discussions and classifications did not lead to the identification of new entities, dimensions, or characteristics.

Step 9e: Consequently, we did not change any of the characteristics and dimensions of our taxonomy.

Step 10: Thus, we also did not revise the taxonomy.

Step 11: As a result, iteration 4 also met the last two open objective endings conditions ("no new dimensions or characteristics were added in the last iteration" and "no dimensions or characteristics were merged or split in the last iteration"). As all objective ending conditions were met and the authors agreed that the taxonomy fulfilled all subjective ending conditions ("concise", "robust", "comprehensive", "extendible", and "explanatory"), we decided to terminate the taxonomy development process after this iteration (Nickerson et al. 2013). Thus, the final version of our taxonomy comprises 3 entities, 11 dimensions and 41 characteristics.

Appendix 3: External Taxonomy Evaluation

To evaluate our taxonomy, we performed eight semi-structured interviews with experts from practice and academia (see Tab. A. 2). In these interviews, we discussed both the taxonomy itself and its application to human-AI hybrids. Based on these interviews, we revised and refined the dimensions and the characteristics of our taxonomy (Step 10) (Kundisch et al. 2022).

Table A. 2: Overview of interviews

ID	Role of the Interview Partner	Industry/ Research focus
I1	Chief Enterprise Architect	Information and communication technology
I2	Project Manager	Software solutions company
I3	Co-Founder	Real estate information provider
I4	Research Assistant	Research focus on machine learning, medical
I5	Data Scientist	Building society
I6	Assistant to the CIO/COO	Industrial insurance company
I7	Research Assistant	Research focus on machine learning, strategic
I8	Research Assistant	Research focus on data science and business

Additionally, we asked our interviewees about the understandability, completeness, and robustness of our taxonomy as well as its suitability for the real world in relation to its purpose (Sonnenberg and vom Brocke 2012). Thus, we also iteratively optimized our taxonomy based on these evaluation criteria. Our approach enabled us to quickly iterate through relevant changes as we were able to evaluate them with each new interview. In each interview, we also presented a visual representation of our taxonomy highlighting the changes of previous iterations. Thus, we could focus the discussion with our interviewees on those relevant parts. We terminated our evaluation process when our interviewees confirmed that all our evaluation criteria were met. Our final taxonomy comprises 3 entities, 9 dimensions, and 38 characteristics. In the following, we list details on the changes performed after each interview.

Interview 1

- We added *perceiving* as a characteristic to the dimension *AI CF* because this cognitive function is a valid contribution option for AI-enabled systems.
- We renamed the characteristic *mixed* to *agile* in the dimension *form of interworking* because it better describes how a human agent, and an AI-enabled system may interwork.
- We removed *organizing* as a characteristic from the dimension *AI CF* because organizing rather is a composition of a variety of cognitive functions.

Interview 2

- We removed the dimension *paradigm* from the entity *task* because it did not properly fit the purpose of our taxonomy.
- We removed the dimension *process adaptation* from the entity *task* because it is rather related to the environment than to the collaboration between human agent and AI-enabled system.
- We removed the characteristic *mixed* from the dimension *time* because its occurrence in real-world applications is rather unrealistic.
- We removed the dimension *roles of AI* from the layer *AI* because it highly overlaps with the dimension *interplay AI2H*.
- We added the dimension *AI focus* with corresponding characteristics *automation*, *augmentation*, and *optimization* to the entity *AI* to account for AI-enabled systems' different areas of focus.
- We removed the dimension *roles of humans* from the entity *human* because it highly overlaps with the dimension *interplay H2AI*.
- We added the dimension *human focus* with corresponding characteristics *sensemaking*, *creativity*, *compassion*, and *utility* to the entity *human* to account for human agents' different areas of focus.
- We renamed the characteristic *communicating* to *interacting* in the dimension *AI CF* because it better describes the level of the cognitive function.

- We added the characteristic *reasoning* to the dimension *human CF* because human agents may also contribute to human-AI hybrids with their ability of reasoning.
- We removed the characteristic *problem-solving* from the dimension *human CF* because *problem-solving* rather is enabled by different cognitive functions.

Interview 3

- We removed the characteristic *judging* from the dimension *human CF* because *judging* also rather is enabled by different cognitive functions.
- We renamed the characteristic *evaluate* to *audit* in the dimension *interplay H2AI* because it is more precise and enables a description of a broader set of applications.

Interview 4

- We renamed the characteristic *AI and human learn* to *AI and human learn separately* in the dimension *learning* to avoid confusion.
- We renamed the dimension *AI CF* to *AI cognitive functions* in the layer *AI* to increase understandability and to avoid unnecessary abbreviations.
- We also renamed the dimension *human CF* to *human cognitive functions* in the layer *human* for the same reason.
- We added a column to our taxonomy to indicate whether dimensions are mutually exclusive.

Interview 5

- We added the characteristic *none* to the dimension *learning* because it is possible that neither the human agent nor the AI-enabled system learns in specific settings.
- We renamed the characteristic *correcting* to *verifying* in the dimension *interplay AI2H* because *verifying* better describes the interplay of an AI-enabled system toward a human agent.
- We renamed the characteristic *auditing* to *verifying* in the dimension *interplay H2AI* because this characteristic describes an analogous interplay for both human agents and AI-enabled systems.

- We reordered the characteristics in the dimensions *interplay AI2H*, *interplay H2AI*, *AI cognitive functions*, and *human cognitive functions* in an ascending ordinal order because of comprehensibility.

Interview 6

- We renamed the characteristic *agile* to *flexible* in the dimension *form of interworking* because the term agile implicates properties that are not directly related to human-AI hybrids.
- We removed the characteristic *optimization* from the dimension *AI focus* because it does not reflect the same level of granularity as augmentation and automation.
- We renamed the dimension *interplay AI2H* to *interaction AI to human* in the entity *AI* to increase the comprehensibility of our taxonomy.
- We renamed the characteristic *guide* to *facilitate* in the dimension *interaction AI to human* because this term better reflects the supporting manner of interaction toward human agents.
- We renamed the dimension *interplay H2AI* to *interaction human to AI* in the entity *human* to increase the comprehensibility of our taxonomy.
- We renamed the characteristic *utility* to *flexibility* in the dimension *human focus* because this term better represents the actual focus of human agents.

Interview 7

- We renamed the entity *task* to *process* because the collaboration process better reflects the overarching dimensions of human-AI hybrids.
- We added the characteristics *perceiving*, *predicting*, *planning*, and *interacting* to the dimension *human cognitive functions* because human agents are also able to perform such functions.
- We added the characteristic *explaining* to the dimension *human cognitive functions* because human agents contribute their ability to explain complex circumstances to human-AI hybrids.
- We removed the dimension *time* in the entity *process* because it proved difficult to determine the specific characteristics when analyzing human-AI hybrids.

- We added a dimension *mode of interworking* with corresponding characteristics *singular* and *continuous* to the entity *process* because this dimension provides important distinctions concerning the interworking of human agents and AI-enabled systems.

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- We removed the characteristic *replace* from the dimension *interaction AI to human* because this characteristic overlaps strongly with the characteristic *supplementing*.
- We removed the characteristic *improve* from the dimension *interplay human to AI* because this characteristic overlaps strongly with the characteristic *facilitating*.

In line with Kundisch et al. (2022), we decided to re-examine recent literature in the field of sociomateriality after evaluating our taxonomy. Based on this examination and intensive discussions in the author team, we decided to rename the entity *process* to *sociomaterial practices* to increase the comprehensibility of our taxonomy and better reflect sociomateriality as our justificatory knowledge.

Appendix 4: Internal Taxonomy Validation

For a final validation of our taxonomy, three of the authors classified a random sample of thirteen human-AI hybrids as the basis for calculating the quality of agreement using Fleiss' (1971) kappa coefficient. All authors used the same sources from our sample to ensure comparability. We achieved inter-coder reliability of 65,90% equally weighted among all dimensions. Since a Fleiss' (1971) kappa between 61% and 80% reflects a "substantial" strength of agreement among all coders (Landis and Koch 1977), we can confirm the reliability of our taxonomy.

Appendix 5: Analysis of Classified Human-AI Hybrids

Figure A. 2: Correlation matrix of all variables resulting from our 101 classified human-AI hybrids

Appendix 6: Clustering of Human-AI Hybrids

Clustering the classified sample of human-AI hybrids built the basis for deriving archetypes. Before being able to accomplish that, however, we needed to determine the number of clusters. We calculated the ideal number of clusters based on various metrics, including but not limited to the Calinski-Harabasz index, the Davies-Bouldin index, the gap statistic, and the silhouette coefficient (Calinski and Harabasz 1974; Davies and Bouldin 1979; Rousseeuw 1987; Tibshirani et al. 2001). According to early indications, the ideal number of clusters appeared to lie between three and seven. Having analyzed the resulting dendrogram (see Figure A. 3), we determined five to be the appropriate number of clusters in our case (Aldenderfer and Blashfield 1984).

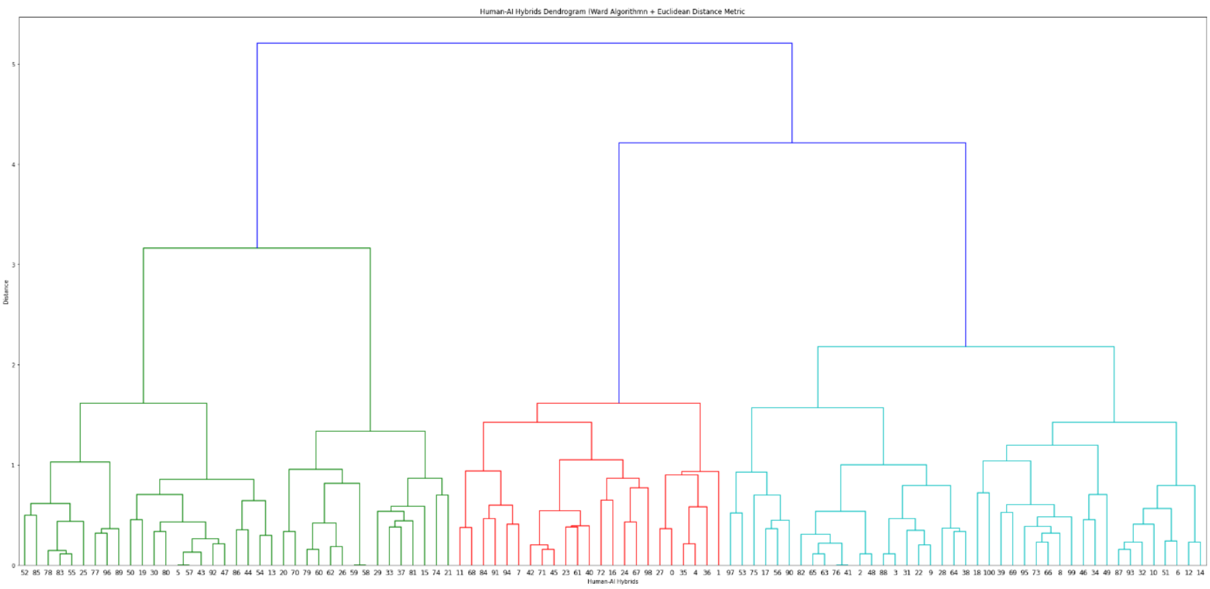

Figure A. 3: Dendrogram of human-AI hybrids clusters based on the Ward's method

Appendix 7: Overview of Human-AI Hybrid Archetypes

Fig. A. 4 to A. 8 display the classification percentages (c) within our archetypes of human-AI hybrids. Characteristics in bold with dark gray background have been found in greater than or equal to sixty-six percent of our sample's cases (bold characteristic c ≥ 66%). Characteristics in italics with light gray background have been found in less than sixty-six percent but greater than or equal to thirty-three percent of our sample's cases (italic characteristic 66% > c ≥ 33%). Characteristics without special formatting have been found in less than thirty-three percent of cases (standard characteristic c < 33%).

Archetype 1: Sequential Automation (AI Pre-Worker)

Layer 1: Sociomaterial entities	**Layer 2: Dimensions**		**Layer 3: Characteristics**								
Human (human agency)	Human cognitive functions	NE	Perceiving (7%)	*Reasoning (60%)*	Predicting (0%)	Planning (0%)	*Decision-making (60%)*	Explaining (7%)	*Interacting (40%)*	Creating (7%)	Empathizing (7%)
	Interaction human to AI	ME	Facilitating (13%)	*Verifying (40%)*	*Supplementing (47%)*						
	Human focus	ME	**Sensemaking (73%)**	Creativity (7%)	Compassion (7%)	Flexibility (13%)					
AI (material agency)	AI cognitive functions	NE	Perceiving (20%)	**Reasoning (93%)**	Predicting (27%)	Planning (7%)	Decision-making (7%)	Interacting (7%)	Creating (20%)		
	Interaction AI to human	ME	Facilitating (20%)	Verifying (7%)	**Supplementing (73%)**						
	AI focus	ME	**Automation (100%)**	Augmentation (0%)							
Sociomaterial practices	Form of interworking	ME	Parallel (0%)	**Sequential (100%)**	Flexible (0%)						
	Mode of interworking	ME	**Singular (100%)**	Continuous (0%)							
	Learning	ME	None (20%)	AI learns (13%)	Human learns (27%)	*Human and AI learn separately (40%)*	Co-evolution (0%)				

c ≥ 66%
66% > c ≥ 33%
c < 33%

Figure A. 4: Sequential automation (AI pre-worker) archetype

Archetype 2: Parallel Automation (Outsourcing AI)

Layer 1: Sociomaterial entities	Layer 2: Dimensions		Layer 3: Characteristics								
Human (human agency)	Human cognitive functions	NE	Perceiving (17%)	*Reasoning (48%)*	Predicting (4%)	Planning (4%)	Decision-making (30%)	Explaining (9%)	*Interacting (48%)*	Creating (9%)	Empathizing (4%)
	Interaction human to AI	ME	Facilitating (26%)	Verifying (13%)	*Supplementing (61%)*						
	Human focus	ME	*Sensemaking (65%)*	Creativity (4%)	Compassion (4%)	Flexibility (26%)					
AI (material agency)	AI cognitive functions	NE	*Perceiving (52%)*	**Reasoning (74%)**	Predicting (30%)	Planning (13%)	Decision-making (22%)	*Interacting (35%)*	Creating (9%)		
	Interaction AI to human	ME	Facilitating (13%)	Verifying (4%)	**Supplementing (83%)**						
	AI focus	ME	**Automation (100%)**	Augmentation (0%)							
Sociomaterial practices	Form of interworking	ME	*Parallel (43%)*	Sequential (26%)	Flexible (30%)						
	Mode of interworking	ME	Singular (0%)	**Continuous (100%)**							
	Learning	ME	None (17%)	AI learns (17%)	Human learns (13%)	*Human and AI learn separately (39%)*	Co-evolution (13%)				

Figure A. 5: Parallel automation (outsourcing AI) archetype

Archetype 3: Sequential Augmentation (Superpower-Giving AI)

Layer 1: Sociomaterial entities	Layer 2: Dimensions		Layer 3: Characteristics								
Human (human agency)	Human cognitive functions	NE	Perceiving (5%)	*Reasoning (59%)*	Predicting (0%)	Planning (5%)	*Decision-making (59%)*	Explaining (5%)	*Interacting (36%)*	Creating (0%)	Empathizing (14%)
	Interaction human to AI	ME	Facilitating (0%)	Verifying (23%)	**Supplementing (82%)**						
	Human focus	ME	**Sensemaking (73%)**	Creativity (0%)	Compassion (14%)	Flexibility (14%)					
AI (material agency)	AI cognitive functions	NE	Perceiving (18%)	**Reasoning (95%)**	**Predicting (77%)**	Planning (0%)	Decision-making (5%)	Interacting (0%)	Creating (9%)		
	Interaction AI to human	ME	*Facilitating (59%)*	Verifying (0%)	*Supplementing (41%)*						
	AI focus	ME	Automation (0%)	**Augmentation (100%)**							
Sociomaterial practices	Form of interworking	ME	Parallel (0%)	**Sequential (100%)**	Flexible (0%)						
	Mode of interworking	ME	**Singular (100%)**	Continuous (0%)							
	Learning	ME	None (18%)	AI learns (9%)	*Human learns (55%)*	Human and AI learn separately (18%)	Co-evolution (0%)				

Figure A. 6: Sequential augmentation (superpower-giving AI) archetype

Archetype 4: Sequential Co-Evolution (Assembly Line AI)

Layer 1: Sociomaterial entities	Layer 2: Dimensions		Layer 3: Characteristics								
Human (human agency)	Human cognitive functions	NE	Perceiving (19%)	*Reasoning (62%)*	Predicting (0%)	Planning (0%)	*Decision-making (62%)*	Explaining (10%)	*Interacting (33%)*	Creating (5%)	Empathizing (0%)
	Interaction human to AI	ME	Facilitating (5%)	Verifying (10%)	**Supplementing (86%)**						
	Human focus	ME	*Sensemaking (52%)*	Creativity (19%)	Compassion (5%)	Flexibility (24%)					
AI (material agency)	AI cognitive functions	NE	*Perceiving (33%)*	**Reasoning (100%)**	**Predicting (71%)**	Planning (5%)	Decision-making (5%)	Interacting (10%)	Creating (10%)		
	Interaction AI to human	ME	**Facilitating (71%)**	Verifying (0%)	Supplementing (29%)						
	AI focus	ME	Automation (0%)	**Augmentation (100%)**							
Sociomaterial practices	Form of interworking	ME	Parallel (0%)	**Sequential (100%)**	Flexible (0%)						
	Mode of interworking	ME	Singular (0%)	**Continuous (100%)**							
	Learning	ME	None (10%)	AI learns (0%)	Human learns (29%)	Human and AI learn separately (19%)	*Co-evolution (43%)*				

Figure A. 7: Sequential co-evolution (assembly line AI) archetype

Archetype 5: Flexible Co-Evolution (Collaborator AI)

Layer 1: Sociomaterial entities	Layer 2: Dimensions		Layer 3: Characteristics								
Human (human agency)	Human cognitive functions	NE	Perceiving (20%)	*Reasoning (35%)*	Predicting (0%)	Planning (5%)	Decision-making (25%)	Explaining (5%)	**Interacting (70%)**	Creating (10%)	Empathizing (15%)
	Interaction human to AI	ME	Facilitating (5%)	Verifying (5%)	**Supplementing (90%)**						
	Human focus	ME	Sensemaking (15%)	Creativity (10%)	Compassion (15%)	*Flexibility (60%)*					
AI (material agency)	AI cognitive functions	NE	*Perceiving (50%)*	**Reasoning (80%)**	*Predicting (50%)*	Planning (15%)	Decision-making (10%)	Interacting (30%)	Creating (5%)		
	Interaction AI to human	ME	*Facilitating (50%)*	Verifying (0%)	*Supplementing (50%)*						
	AI focus	ME	Automation (0%)	**Augmentation (100%)**							
Sociomaterial practices	Form of interworking	ME	Parallel (15%)	Sequential (0%)	**Flexible (85%)**						
	Mode of interworking	ME	Singular (0%)	**Continuous (100%)**							
	Learning	ME	None (5%)	AI learns (0%)	*Human learns (35%)*	Human and AI learn separately (25%)	*Co-evolution (35%)*				

Figure A. 8: Flexible co-evolution (collaborator AI) archetype

Appendix 8: Archetype Evaluation

To assess their reliability and validity, we evaluated our archetypes by performing an internal Q-Sort. Two co-authors who were not yet familiar with the results of agglomerative clustering achieved an overall hit ratio of 100% (Moore and Benbasat 1991). The archetype-specific hit ratios also were 100%, which indicates a perfectly correct classification of the random sample of 25 human-AI hybrids. Moreover, the co-authors achieved a Cohen's (1960) kappa coefficient of 100%. Both the results of the hit ratios and Cohen's (1960) kappa coefficient represent a perfect agreement (Landis and Koch 1977). As a result, we regard our archetypes of human-AI hybrids as valid and reliable.

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