Designing Human-AI Hybrids: Challenges and Good Practices from a Multiple Case Study

Completed Research Paper

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Abstract

The increasing adoption of artificial intelligence (AI) in organizations has led to the emergence of human-AI hybrids, where human and AI agents collaborate on joint tasks. This paper presents a multiple case study exploring the challenges and good practices of constructing and executing such hybrid systems. Using a work system theory perspective, we identify nine challenges and nine good practices from four successfully implemented real world cases of human-AI hybrids, structured along the work system lifecycle. In line with our socio-technical approach, we identify two major stakeholder roles involved in the construction and execution of human-AI hybrids, the technical implementer and the organizational implementer, each of which faces unique challenges and applies different good practices. This research contributes to the growing body of knowledge on the implementation of human-AI hybrids in organizations and provides practical insights for managers and implementers seeking to successfully integrate AI into their work systems.

Keywords: Human-AI hybrids, work system theory, multiple case study, human-AI collaboration

Introduction

State-of-the-art AI applications can be used via interfaces that are easy to navigate, such as chat interfaces used by ChatGPT or similar tools. Consequently, non-AI experts increasingly use AI applications without detailed knowledge of the underlying technologies. Similarly, organizations are also deploying AI applications in an increasing amount and variety of use cases (Databricks, 2023), where both AI-experts and non-AI-experts are using these applications alike in their daily work processes. This is also often referred to as the democratization of AI technologies (García-Peñalvo and Vázquez-Ingelmo, 2023; Kanbach et al., 2024). As discussed in the IS literature, these AI applications are becoming increasingly agentic in such work systems (Baird and Maruping, 2021; Berente et al., 2021), to the extent that they are referred to as AI agents or, more generally, intelligent agents (Berente et al., 2021; Jakob et al., 2024). Thus, the purposeful implementation of organizational settings (hereafter referred to as *work system*) where human agents are collaborating with AI agents on a joint process or task (hereafter referred to as *human-AI hybrid*) is becoming an important concern for organizations seeking to leverage the capabilities of AI applications (Fabri et al., 2023; Jakob et al., 2024; Stohr et al., 2024).

Similarly, a research stream on the design of human-AI hybrids has emerged in the academic discourse (Caldwell et al., 2022; Echeverria et al., 2023; Raisch and Fomina, 2024). Existing research has identified archetypes of organizational settings using human-AI hybrids (Fabri et al., 2023) and has also created frameworks that seek to structure the design space of organizational settings that use collaboration between human and AI agents (Braun et al., 2023; Fuchs et al., 2024; Jakob et al., 2024; Zercher et al., 2023). Braun et al. (2023) take a teamwork perspective on human-AI hybrids and use a literature review to develop a framework that describes the temporal phases of their collaboration. The framework portrays mechanisms of human-AI teamwork for different teamwork phases. While offering important insights, it does not provide guidance on how to design the work system in which the collaboration occurs. In contrast, the framework by Jakob et al. (2024) builds on the work system perspective and identifies 16 dimensions that structure the design space for work systems that use collaboration between human and AI agents but does not provide actionable insights into how to use the dimensions throughout the lifecycle of the work system.

We, therefore, conclude that while we have theoretical insights into the lifecycle phases and the dimensions of the design space for work systems that use human-AI hybrids, currently we do not have fundamental insights into good practices and challenges that organizations are using or facing when seeking to implement a work system where humans collaborate with AI agents. This gap in research is particularly relevant to address, as many attempts to create work systems that utilize collaboration between human and AI agents still fail due to a lack of consideration of socio-technical factors (Asatiani et al., 2021) and uncertainties regarding the integration with existing work systems (Lee et al., 2023; Shollo et al., 2022; Stohr et al., 2024; Weber et al., 2023). As long as we do not have structured empirical insights into practices and challenges of constructing and executing work systems using human-AI collaboration, we are not able to transfer the existing theoretical knowledge on collaborative human-AI hybrids into practice, risking a disconnect between research and practice and the lack of cumulative knowledge building by further advancing theory from empirical interventions. In consequence, currently constructed human-AI hybrids may not perform better than purely human or AI-based work systems (Hemmer et al., 2024). Thus, we ask:

What are the challenges and good practices for the construction and execution of human-AI hybrids?

To approach this research goal, we conducted a multiple case study of successfully constructed and executed human-AI hybrid implementations to derive good practices and challenges out of their experience. For our study, we investigated cases from different industries with different levels of criticality of the process or task carried out by the human-AI hybrid and with different AI technologies being used to build the human-AI hybrid. In doing so, we are confident that we could gather insights that apply to a broad range of different types of human-AI hybrids. By documenting nine challenges and nine good practices of human-AI hybrid design, our results address a call by Fabri et al. (2023) for empirical insights into the design of human-AI hybrids. We reveal two distinct roles in the design of human-AI hybrids, the organizational and the technical implementer, each of which faces a different set of challenges. Further, by structuring the process of human-AI hybrid design into the construction and execution phase, our results reveal that during the construction phase, successful implementations focus on the architecture of the human-AI hybrid (i.e., aspects such as the used infrastructure, technologies, and the overall organizational strategy), whereas during the execution phase, the focus shifts towards the participants (both human and AI agents) of the human-AI hybrid and their collaboration on the joint task or process. Therefore, our results highlight opportunities for future research by laying the foundation for developing human-AI hybrid design theory. Finally, our results also provide insights for practitioners seeking to implement human-AI hybrids in their organizations.

This paper is structured as follows. Section 2 presents the theoretical foundations by elaborating our understanding of human-AI hybrids and by introducing the work system theory that we built our research model on. In Section 3, we describe the research method underlying our multiple case study in detail. Section 4 presents the results of our study, followed by the discussion of implications that these results may have in Section 5. Finally, Section 6 summarizes our contributions to both theory and practice.

Theoretical Foundation

Human-AI Hybrids

With the introduction of diverse AI technologies, like ChatGPT, humans and AI agents are increasingly working together to achieve complex tasks. This collaborative effort is often referred to as a human-AI hybrid in the academic literature (Caldwell et al., 2022; Fabri et al., 2023; Punzi et al., 2024). Rai et al. (2019) describe human-AI hybrids as the dynamic interplay between human and AI capabilities. The matching of human and artificial intelligence, named hybrid intelligence, then, in the best case, leads to the complementarity of the strengths of both humans and AI agents to improve decision-making and enhance overall performance (Dellermann et al., 2019; Hemmer et al., 2021; Hemmer et al., 2024).

Previous research studied AI agents that, e.g., support teachers and students in managing complex classroom transitions (Echeverria et al., 2023). The findings suggest a hybrid approach where humans and AI agents share control, with AI agents controlling specific tasks or advising on pairings. The study's conclusions provide design directions for the coordination of multiple agents (humans and AI systems) in real time. Further, Raisch and Fomina (2024) discuss the integration of human intelligence with AI to solve complex problems and propose three hybrid problem-solving processes. This aligns with the goals of researchers in the field of human-AI hybrids who aim to develop advanced AI agents that can augment human capabilities and improve various aspects of human work processes. Additionally, Caldwell et al. (2022) develop a research framework that aims to explore human-AI teaming within experimental environments and prepare it for the transfer to real-world contexts. The framework is designed to provide a structure for understanding the macro features of hybrid teams, including acceptability and affordances, with the goal of enhancing decision-making and performance. While these studies conduct empirical research on human-AI hybrids, they focus on the construction of hybrids before the deployment and successful execution of human-AI hybrids or are based on thought experiments. However, for the successful design of human-AI hybrids, we need to explore the construction and execution of human-AI hybrids in real-world scenarios that have been implemented successfully.

Besides these empirical efforts of studying human-AI hybrids and their practical applications, research has also yielded several theoretical frameworks that seek to structure the design space of implementing human-AI hybrids. Braun et al. (2023) conducted a literature review to build a theoretical framework of human-AI collaboration from a teamwork perspective. Their framework structures human-AI collaboration into three phases, *preparation, execution,* and *evaluation* and describes different mechanisms of collaboration during each of these phases. In a similar direction, Zercher et al. (2023) conducted a literature review to investigate how intragroup processes differ in team-AI collaboration compared to processes in human teams. They find that in human-AI collaboration intragroup processes such as communication and coordination tend to be less effective than in human teams and suggest future research to study why this is the case. Finally, Jakob et al. (2024) also conducted a literature review to develop a framework for task-centered human-AI collaboration that structures 16 important design dimensions of human-AI collaboration based on a work system theory perspective. This framework was developed using a theoretical perspective similar to our research endeavor, but it remains mostly theoretical in its contribution. Further, Jakob et al. (2024) do not differentiate between the construction and execution of human-AI hybrids, a distinction we seek to make to reflect the work system lifecycle.

In this paper, we seek to complement these theoretical frameworks based on literature reviews with empirical insights into the implementation of human-AI hybrids. To that end, we distinguish between two key activities of human-AI hybrid implementation: construction and execution. We define construction as the process of designing and developing the human-AI hybrid, including defining requirements, selecting algorithms, and integrating human and AI agents. This understanding is related to the understanding of the *preparation* of human-AI collaboration by Braun et al. (2023). Execution then involves the actual operation of the work system, where human and AI agents work together to achieve a common goal. For example, Oyedeji et al. (2019) describe how human-AI hybrids are already being designed and implemented for medical diagnosis. In this context, construction involves designing hybrid systems that integrate human expertise with AI-driven analytics. Execution involves the actual application of these systems, where clinicians and AI systems work together to diagnose diseases. Since human-AI hybrids are socio-technical systems, we must consider these systems from both a technical and an organizational perspective (Fabri et al., 2023). Therefore, every hybrid system consists of human agents, AI agents, and the organizational structures that govern their interactions (Bostrom and Heinen, 1977; Herrmann and Pfeiffer, 2023).

Work System Theory (WST)

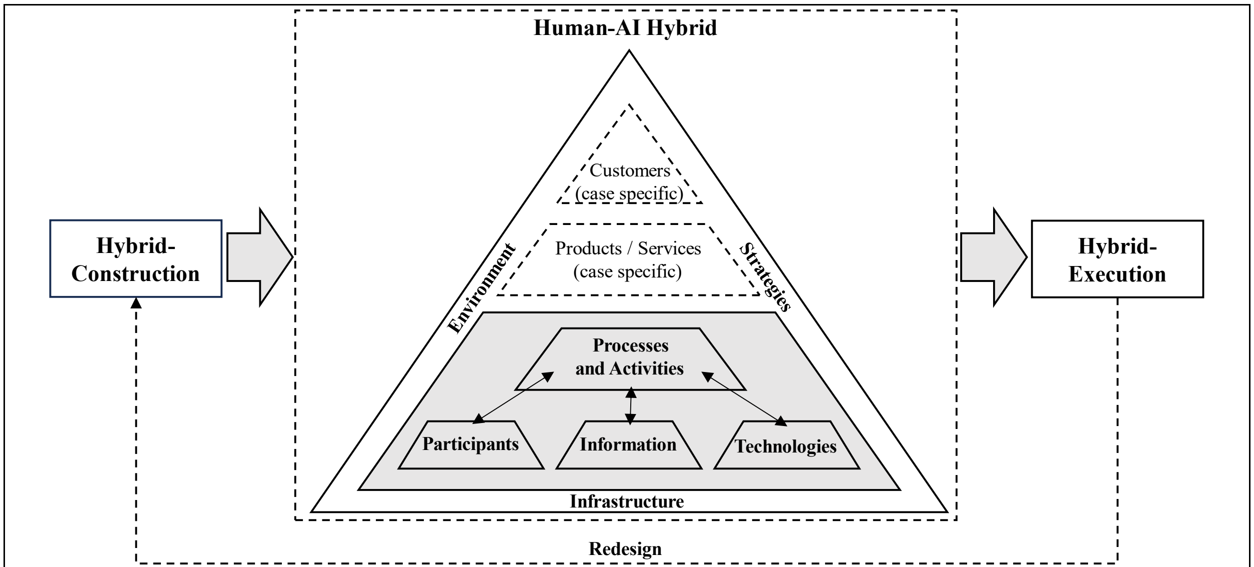

Figure 1. Research Model Based on Work System Theory (Alter, 2013)

The Work System Theory (WST) is a theory that fits our previously mentioned two-phased socio-technical perspective on human-AI hybrids. The term *work system* is widely used in the IS domain (Alter, 2008), with Bostrom and Heinen (1977) using it in their seminal work to describe the socio-technical systems approach. A work system is understood to be an organizational setting in which a process and its associated activities are collaboratively performed by human participants and machines "using information, technology, and other resources to produce specific products/services for specific internal and/or external customers" (Alter, 2013, p.75). Overall, each work system consists of nine elements: *processes and activities, participants, information, technologies, products/services, customers, environment, infrastructure,* and *strategies* (Alter, 2013). WST, therefore, can be described as taking a socio-technical perspective on organizational settings with a defined task to achieve. Further, each work system can be embedded in a bigger work system, allowing a work system to be composed of multiple smaller work systems. A human-AI hybrid may be understood as a specific work system that is embedded in a larger organizational work system, where human participants collaborate with AI agents to perform a certain task or process.

Notably, WST also describes the lifecycle of a work system to be comprised of four phases. These phases are *initiation*, *development*, *implementation*, and *operation and maintenance* (Alter, 2013). These phases fit our approach to designing human-AI hybrids, as *initiation*, *development*, and *implementation* can be subsumed under the hybrid-construction phase while *operation and maintenance* maps onto the hybrid-execution phase. Following WST as described by Alter (2013), a hybrid-execution phase may either be ended by the termination of the human-AI hybrid or it may be followed by another construction phase in cases where an organization decides to redesign or adjust the work system.

While we consider human-AI hybrids to be proper work systems in this paper, in the following, we focus on a subset of the work system elements while studying the construction and execution of human-AI hybrids. These elements are *processes and activities* (also referred to as the *joint task* in the following), *participants*, *information*, *technologies, environment, strategies,* and *infrastructure*. This focus is due to the fact that in our study, we seek to create general insights into the construction and execution of human-AI hybrids, independent from case-specific aspects such as the specific product or service being made or the specific customer being served. Figure 1 depicts our research model, highlighting the two human-AI hybrid phases as well as the elements a human-AI hybrid is comprised of based on WST.

Research Method

Study Approach and Case Descriptions

To approach our research goal of understanding challenges and good practices for the construction and execution of human-AI hybrids, we conducted a multiple case study (Eisenhardt, 1989; Yin, 2014). We collected qualitative data from four cases, which we selected using a convenience sampling approach based on the availability of the cases to the authors, as well as through targeted email outreach to potentially interesting cases found on the internet. To select the cases, we devised three ex-ante sampling criteria: (1) Each case had to construct and execute an AI application in a live organizational setting, (2) the AI application had to be used by or collaborate with a human agent to achieve a clearly defined task in the organizational setting, (3) the implementation of the human-AI hybrid of the case was already finished and considered to be successful. Finally, we also sought to include different types of AI applications (and thus, different types of human-AI hybrids) in our portfolio of selected cases so as not to constrain our insights to any specific type of AI application and thus deliver more generalizable results.

Two of the four cases, Case A and Case B, are concerned with building a collaborative human-AI hybrid designed to support the human agent in accessing and using knowledge. In Case A, a knowledge management solution was built for a manufacturing company of agricultural machinery. Based on semantic search techniques, the AI application supports company technicians with insights into how to troubleshoot and fix machine faults on site for customers. In Case B, the developed AI application is based on a large-language model and is used as an onboarding companion for new employees, answering their questions about the organization and its processes during the first weeks of employment. In contrast, the AI application discussed in Case C is specifically designed to optimize truck route planning and assist truck drivers in managing their resting stops. The application utilizes a sophisticated predictive model that leverages historical data on parking availability to suggest the best possible routes and resting stops. This is crucial because truck drivers are often constrained by regulations that limit their driving hours. Failing to find a parking spot within these designated time slots can lead to severe penalties. By providing real-time predictions on parking availability, this AI tool helps mitigate the risk of such penalties and supports truckers in making more informed decisions about their travel and rest plans. Finally, in Case D, a platform for AI-based crisis management services was built, with a focus on logistics and supply chain management. The platform offers various services for logistic specialists that are accessible through a chat interface and a filtering system that assists logistics employees in evaluating risks and predicting crisis situations. Among others, one of the services is using satellite image data of cargo ship traffic in critical locations (e.g., the Suez Canal) to predict supply chain disruptions.

Data Collection

For each of the four selected cases, we collected rich qualitative data (Yin, 2014). We conducted multiple interviews with people involved in different roles in each case, ensuring that both the organizational and the technical perspectives on the human-AI hybrid are represented by interview partners (Myers and Newman, 2007; Schultze and Avital, 2011). The interview partners were sampled using a theoretical sampling approach (Glaser and Strauss, 2017), where initial interviewees were selected purposely for each case. Once we had conducted the initial interviews and analyzed the first collected data for each case, we asked interview partners to provide us with contacts of further relevant interview partners for the respective case to ensure for each case that we covered both the organizational and technical perspectives. The interviews were semi-structured in nature (Myers and Newman, 2007), allowing us to dynamically adjust the focus of each interview depending on the areas of expertise of the interviewee while ensuring all relevant aspects were touched upon in each interview. All the interviews were audio-recorded with the consent of the interview partners and subsequently transcribed for the coding process. Further, next to the interviews, we collected case data, such as project reports, videos, secondary interviews, websites, etc., for each case, which allowed us to triangulate our findings from the interviews (Yin, 2014). Table 1 summarizes all four cases and the respective data sources that we collected.

Case	No.	Interview partner	Perspective	Interview duration	Case data
Case A: Knowledge management	I1	IP1: Researcher & management consultant	Organizational	63 min	• 1 project website • 1 interim report • 5 factual reports • 3 presentations from steering committee meetings • 1 (technical) demo workshop of AI system
	I2	IP2: Researcher & management consultant	Organizational	64 min	
	I3	IP3: Lead developer	Technical	59 min	
Case B: LLM-based employee onboarding	I4	IP4: Senior IT-Architect	Technical	63 min	• 1 project website • 1 project presentation
	I5	IP5: Lead project manager	Organizational	70 min	
	I6	IP6: Lead developer	Technical	58 min	
Case C: Intelligent parking assistant	I7	IP7: Technical project lead	Technical	33 min	• 1 secondary project interview • 5 project websites • 1 project video by public television • 1 presentation of project challenges and results at conference
	I8			52 min	
	I9	IP8: Organizational project lead	Organizational	60 min	
	I10	IP9: CEO	Organizational	54 min	
Case D: Crisis management	I11	IP10: Researcher & crisis management consultant	Organizational	61 min	• 2 project websites • 1 secondary conference panel interview • 1 whitepaper • 1 magazine article • 1 AI innovation competition report • 1 research article pre-print • 7 research articles • 6 short-clips about offered AI-services
Total:	**11 interviews**	**10 interview partners**		**10h 37 min**	**41 case documents**

Table 1. Overview of Cases and Collected Case Data

Data Analysis

To analyze the collected data, we followed established guidelines for qualitative data analysis (Gioia et al., 2013; Mayring, 1994; Miles et al., 2014). First, to structure the process of data analysis, we used our ex-ante model, which we presented in Section 2, that describes which concepts should be considered to achieve our research goal of identifying challenges and good practices for the construction and execution of human-AI hybrids. Following this model, we analyzed the key challenges and good practices of the human-AI hybrid construction and execution in our four cases, using the concepts *challenge* and *good practice* as the central themes for coding and the concepts *construction* and *execution* as the aggregate dimensions.

We then started to inductively code our data using open and axial coding (Corbin and Strauss, 2015; Gioia et al., 2013). We assigned descriptive codes to significant chunks of data that describe challenging aspects or good practices encountered in the four cases, to summarize these chunks of data with a short phrase

(Miles et al., 2014). Then, we grouped these descriptive codes into one of the four themes: *hybrid construction challenges*, *hybrid construction good practices*, *hybrid execution challenges*, or *hybrid execution good practices*. Figure 2 depicts this process of data analysis.

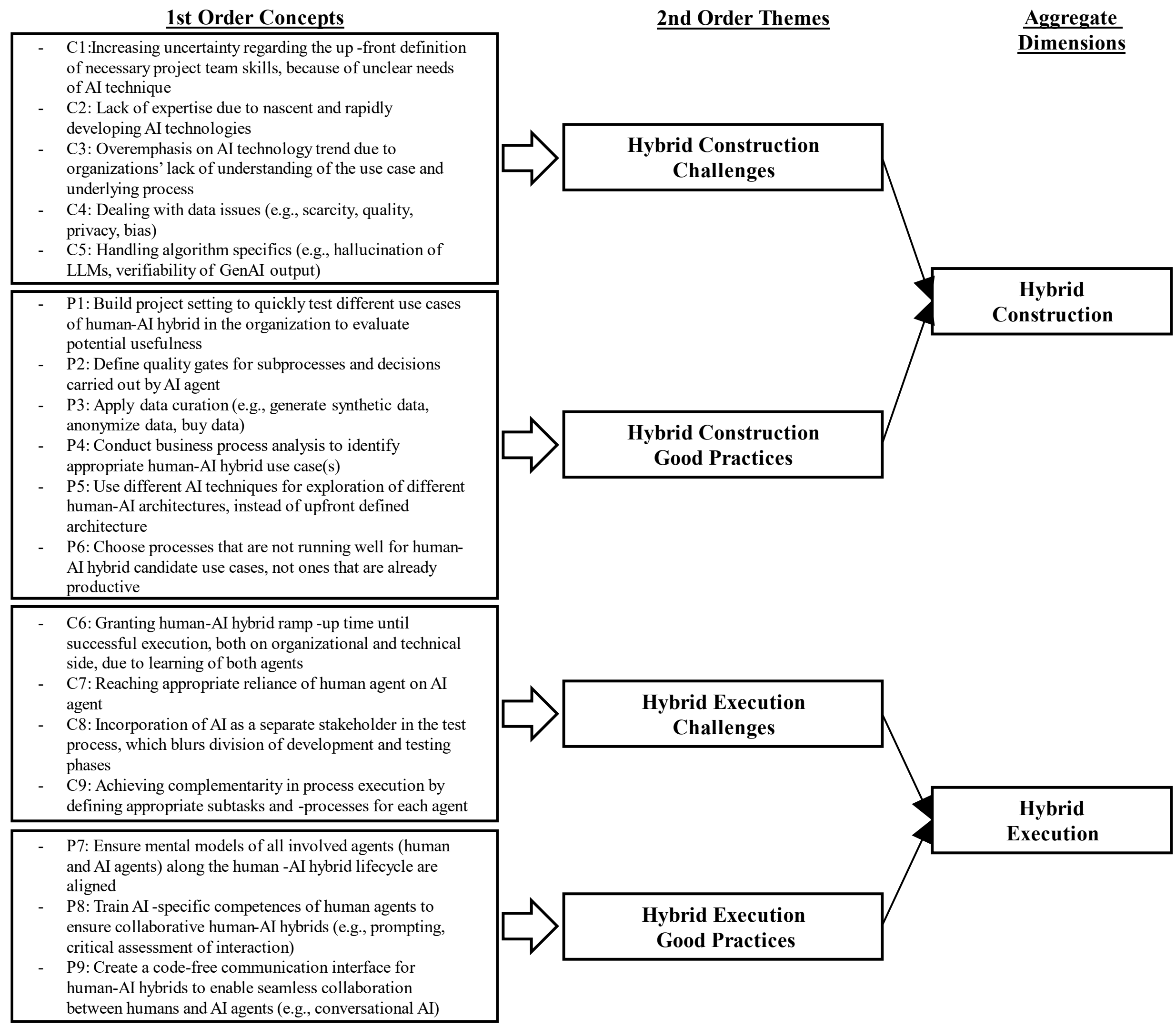

Figure 2. Data Analysis Structure for Identification of Challenges and Good Practices

Subsequently, after this inductive approach of identifying the challenges and good practices, we analyzed the challenges and good practices using our previously presented research model, which is based on the WST. The concepts of the research model (i.e., *processes and activities*, *participants*, *information*, *technologies, environment, strategies,* and *infrastructure)* served as a starting point and interpretive framework for this step, adopting the research technique of sensitizing concepts (Bowen, 2006; Glaser, 1978). These sensitizing concepts provide us with "a general sense of reference and guidance in approaching empirical instances" (Bowen, 2006) in our case data. For each challenge and good practice, we emerged ourselves in the data and analyzed whether they related to any of the sensitizing constructs from our research model. In doing so, we were able to interpret the results from our inductive data analysis from the perspective of our research model.

Results

In the following, we introduce the nine challenges and nine good practices that we identified from our cross-case analysis. The challenges and practices are structured according to the phase in which they occurred, either during the construction or the execution of the human-AI hybrid implementation. Further, for each challenge and practice, we elaborate on the concepts from our WST-based research model that it relates to and to the affected stakeholder. Tables 2, 3, 4, and 5 show the identified challenges and good practices.

The Role of Technical and Organizational Implementers

In line with the WST and the socio-technical lens of our research model (Alter, 2013; Bostrom and Heinen, 1977), we differentiate the stakeholders involved in the construction and execution of human-AI hybrids into **organizational** and **technical implementers**. The organizational implementers include stakeholders responsible for orchestrating the successful integration of the human-AI hybrid into the organization's processes. This involves, among other tasks, the development and execution of change management, business process analysis, ensuring stakeholder engagement, and providing training and support for human agents in the human-AI hybrid to ensure a seamless incorporation of the human-AI hybrid in the organization. Technical implementers include stakeholders responsible for installing, configuring, and testing the AI agents of the human-AI hybrid. Among others, technical implementers need expertise in software development and data analytics to ensure the implementation meets functional and performance requirements of the human-AI hybrid. For some of the challenges and good practices, we identified a higher need for their collaboration than in others, as indicated in the stakeholder column of Tables 2 through 5. Based on WST, in the following, for each of the identified challenges and good practices we also describe which of the work system elements are related to the respective challenge or good practice. This analysis helps to understand which aspects of a work system should be considered and by whom (i.e., organizational or technical implementers) in order to address a challenge or implement a good practice.

Challenges of Human-AI Hybrid Construction

No.	Description	Stakeholder	Relation to WST research model	Source
C1	Increasing uncertainty regarding the up-front definition of necessary project team skills, because of unclear needs of AI technique	Tech. implementer, Org. implementer	Participants	Case C, Case D
C2	Lack of expertise due to nascent and rapidly developing AI technologies	Org. implementer	Participants	Case A, Case C, Case D
C3	Overemphasis on AI technology trend due to organizations' lack of understanding of the use case and underlying process	Org. implementer	Processes and Activities, Strategies	Case A, Case D
C4	Dealing with data issues (e.g., scarcity, quality, privacy, bias)	Tech. implementer, Org. implementer	Information, Infrastructure	Case A, Case B, Case C, Case D
C5	Handling algorithm specifics (e.g., hallucination of LLMs, verifiability of GenAI output)	Tech. implementer, Org. implementer	Technologies	Case A, Case B

Table 2. Identified Challenges of Human-AI Hybrid Construction

The construction of human-AI hybrids often begins with uncertainty regarding the required skills and expertise of the project team (*C1*). As the AI term is an umbrella term that covers vastly different technologies (Ågerfalk et al., 2022; Grashoff and Recker, 2023), interviewees described that it is hard to decide in the beginning of a project which experts will be needed for constructing the hybrid due to the evolving nature and variety of AI technologies. IP10 said: "*I think what is a challenge, especially perhaps in the development of AI systems, is the size of a consortium. [...] Do you have the right experts? Because you also have to think relatively far ahead, sometimes very deeply into a subject.*" The challenge thus relates to the *participants* of the work system. It is also directly linked to the second challenge of constructing human-AI hybrids (*C2*), which also is related to the *participants* in the work system. Interviewees from cases A, C, and D described to us the current lack of expertise in AI technologies due to their nascent and rapidly evolving nature. As AI technologies continue to evolve at a rapid pace, organizations struggle to recruit skilled employees or upskill their teams as needed. Interviewee IP2 explained: "*And then the next challenge was what I briefly mentioned earlier. The deployers were significantly less well trained than they expected. [...] although we already had a very integrated, ML-Ops-optimized solution, for example for metadata labelling, where you actually just have to run a script. And that, for example, was already a problem [...]*".

Further, we found that many organizations involved in the cases of our study wanted to implement AI hybrids for the sake of the AI trend rather than to solve an ongoing issue with a fitting technology. This is similar to the concepts of technology push versus market pull (*C3*). Interviewee IP1, responsible for scientific organizational guidance at Case A, described that this was often a challenge with industry partners: "*At the beginning we were with one of our application partners, where the managing director was also present [...] and at some point, he became relatively impatient, because at the beginning of the project we focused very much on the basics, saying what is your process?*" Therefore, we relate this challenge to understanding the *processes and activities* of the work system, as well as the overall *strategy* of the organization. Relating to challenge C3, also data issues were described to us as challenges regarding the *information* and *infrastructure* of the work system in all four cases of our study (*C4*). While all organizations involved in the studied cases were eager to apply AI technologies, in all cases interviewees described to us situations where data was not available in a condition necessary to proceed with AI application development. Interviewee IP7 described: "*This problem arose during the solution design phase, namely that we needed a large amount of highly precise data, and we simply didn't get enough."* Similarly, interviewee Ip10 described that even anonymization efforts did not alleviate this challenge: "*We have worked a lot with anonymization [...]. In some cases, however, this is simply not enough to create trust for companies. Of course, if there are companies involved that are in competition, it becomes even more difficult. That's a huge problem.*" Data curation strategies, such as highlighted in practice *P3*, are therefore essential for ensuring the successful construction of AI applications.

Finally, interviewees also described algorithm-specific challenges such as hallucination in the case of LLMs during the construction of their human-AI hybrids (*C5*), relating to the *technologies* of the work system. IP5 described, that while such algorithm-specific challenges may occur, they typically require a management trade-off between the potential severity of consequences resulting from algorithm-specific problems and the potential benefit that the AI application may provide to the hybrid work system: "*In terms of organization, I always say, well, it is of course desirable that nothing is wrong and that no hallucinations come out. But that is also a management objective where you have to look at the individual scope [of the project] to see whether it improves the status quo.*"

While challenge *C2* was identified as important in the context of our human-AI hybrid cases, we consider it to not be exclusively relevant in AI-related cases. Lack of expertise in dealing with newly emerging technologies can be considered a general challenge of organization seeking to lever the capabilities of these technologies. However, as AI technologies are developing rapidly this might be particularly challenging in the AI context.

Good Practices of Human-AI Hybrid Construction

Besides the challenges, we also identified five good practices for human-AI hybrid constructions from our multiple case study. The first practice we identified, relating to the *processes and activities* of the work system as well as the overall organizational *strategy*, is to build a project setting that allows to quickly test different use cases of human-AI hybrids in the organization, in order to evaluate their potential usefulness and strategy fit (*P1*). This practice, aligning with practices from rapid prototyping and agile development, allows organizations to iteratively refine their use case and approach towards constructing a human-AI hybrid based on early feedback. This also refers to challenge C3, ensuring identification of an appropriate organizational use case for human-AI hybrids before starting with the technology part. IP1 described their project setting accordingly: "*This is also something that made the project strong in this respect, because you could quickly test many use cases. So, you could simply upload a few data sets quickly, then carry out an experiment, try it out, see how well it went? Did it go badly? [...] And then play through the next use case or go through the next use case.*" The second identified practice is to define quality gates for the subprocesses and decisions carried out by the AI agent (*P2*). This practice relates to the *processes and activities* and the *environment* of the work system, as only quality-ensured work results should be passed to the environment beyond the human-AI hybrid work system. IP4, for example, mentioned measures that were implemented by the technical implementer in Case B: "*But what we had to build there are links to product pages, because we couldn't rely on the chatbot to really cleanly extract all the numbers or really provide the information that the user needs at that point. This means that we have to offer further information and then build an additional system that extracts this information or provides suitable links.*" However, besides technology-based measures also organizational quality gates such as a review of an AI agents work by a human expert can be introduced by the organizational implementer. Overall, this practice is especially important as AI agents are autonomous but cannot be made responsible for failures. Since humans are responsible for the mistakes of AI agents, it makes sense to ensure quality by keeping a human in the loop for critically assessing AI's work.

No.	Description	Stakeholder	Relation to WST research model	Source
P1	Build project setting to quickly test different use cases of human-AI hybrid in the organization to evaluate potential usefulness	Org. implementer	Processes and Activities, Strategies	Case A, Case B
P2	Define quality gates for subprocesses and decisions carried out by AI agent	Tech. implementer, Org. implementer	Processes and Activities, Environment	Case A, Case B
P3	Apply data curation (e.g., generate synthetic data, anonymize data, buy data)	Tech. implementer	Information, Infrastructure, Environment	Case C, Case D
P4	Conduct business process analysis to identify appropriate human-AI hybrid use case(s)	Org. implementer	Processes and Activities, Participants	Case A, Case B, Case C
P5	Use different AI techniques for exploration of different human-AI architectures, instead of upfront defined architecture	Tech. implementer	Technologies, Participants, Infrastructure	Case B, Case C, Case D
P6	Choose processes that are not running well for human-AI hybrid candidate use cases, not ones that are already productive	Org. implementer	Processes and Activities, Strategies	Case A, Case B

Table 3. Identified Good Practices of Human-AI Hybrid Construction

As all cases of our studies faced data-related issues (*C4*), we also observed data curation being applied by the technical implementer as a practice to alleviate these challenges in their efforts to construct human-AI hybrids (*P3*), such as using synthetic data to face the issue of data scarcity. These practices seek to ensure proper *information* availability for the work system, by building on data *infrastructure* in the work system *environment*. This includes the generation of synthetic data and the acquisition of data via data brokers, but also include redefinition of the human-AI hybrid use case such that publicly available data could be used to achieve the desired outcome. Relating on challenge C3, we observed from multiple cases that conducting a thorough business process analysis is essential for identifying suitable human-AI hybrid use cases and to pinpoint areas where AI can add value (*P4*). Regarding the work system, this ensures a proper understanding of the *processes and activities* and *participants'* roles. Interviewee IP1, as organizational implementer, detailed their process analysis approach in Case A: "*We carried out process modelling at the companies and looked at what a typical workflow looks like for them in order to see where the employees are actually doing search tasks. [...] And it was precisely in this context that we also looked at: How often is this process instantiated? What are the normal throughput times? Is there an idle time somewhere? How many stakeholders are involved in the process? Etc. We also used this afterwards to challenge the economic perspective.*"

We also observed the practice of using different AI techniques for the exploration of different human-AI hybrid architectures (*P5*). IP7 as a technical implementer suggested that, instead of defining a specific architecture and AI techniques for the human-AI hybrid upfront, they relied on the possibility of exploratively applying different AI techniques and technologies to the respective use cases in Case C. In doing so, they iteratively discarded the AI techniques and technologies that performed worse in the given use case (i.e., not necessarily regarding hard KPIs of AI model performance like, e.g., accuracy but also judging performance in context of collaboration with humans in the work system). This practice emphasizes experimentation and adaptation and relates to the *technologies* and *infrastructures* used to create collaboration among human and AI *participants* in the work system. Finally, when selecting use cases or processes for human-AI hybrid application, the organizational implementer should consider processes in the organization that are currently not running well over ones that are already productive (*P6*). Thus, this practice relates to the *processes and activities* of the work system and the organizational *strategy* for AI usage. In line with the common saying to never change a running system, IP1 described: "*In my opinion, if there is pressure for support, a solution is perceived very differently than if you are trying to improve an everyday process that is already working well from the user's point of view.*"

Even though all of these practices were identified as relevant in the context of our cases focused on human-AI hybrids, the practices *P1*, *P4*, and *P6* seem to be also applicable in non-AI cases. Agile, iterative testing of use cases, conducting proper business process analysis, as starting to test new technologies in use cases that are not already productive are equally important in other digital technology initiatives. This highlights that not only AI-specific practices are of relevance in pursuit of human-AI hybrid construction, but also practices related to other IT-initiatives.

Challenges of Human-AI Hybrid Execution

No.	Description	Stakeholder	Relation to WST research model	Source
C6	Granting human-AI hybrid ramp-up time until successful execution, both on organizational and technical side, due to learning of both agents	Tech. implementer, Org. implementer	Participants	Case A, Case B
C7	Reaching appropriate reliance of human agent on AI agent	Org. implementer	Participants	Case A, Case B, Case C
C8	Incorporation of AI as a separate stakeholder in the test process, which blurs division of development and testing phases	Tech. implementer, Org. implementer	Participants	Case C, Case D
C9	Achieving complementarity in process execution by defining appropriate subtasks and -processes for each agent	Org. implementer	Participants, Processes and Activities	Case A, Case B

Table 4. Identified Challenges of Human-AI Hybrid Execution

During the execution phase of human-AI hybrids, it is essential to recognize that both the human and AI agents require a ramp-up period to ensure successful execution (*C6*). This challenge therefore relates to the work system *participants* and arises from the need for both agents to learn from each other and adapt to their new collaborative roles. It shows that organizations need to see AI agents as own identities that need time to adapt and learn, just like human agents. Our cases A and B illustrate this, as both the knowledge management tool and the onboarding companion required time for human agents to become familiar with the AI applications' capabilities and limitations. Similarly, AI application performance increased over time, as the AI applications were learning with continued use. IP4 explained: "*At the end of the day, it doesn't just depend on the technical circumstances, but also on the way people ask questions, because sometimes the smallest changes in a question can lead to different answers. So, it's very complex [...]*". This directly relates to the next challenge (*C7*), achieving appropriate reliance, i.e., “the human‘s ability to differentiate between correct and incorrect AI advice and to act upon that discrimination” (Schemmer et al., 2022, p. 2). Our cases demonstrate, that during execution of the human-AI hybrid it is often hard for human agents to judge the AI agents' capabilities and limitations and therefore achieve appropriate reliance in the work system.

Further, we observed the challenge that with usage of AI technologies the separation between construction and execution of work systems becomes increasingly blurred (*C8*). IP7 described that AI is playing a role as an active stakeholder both in development and execution of the work system: "*I used to be happy if the customer didn't complain, but now I'm happy if the customer complains because it means I can really* *improve my system automatically. [...] I would say that AI plays a role, both as support in solution development and as feedback during test runs.*" This challenge therefore relates to the *participants* of the work system. Finally, we also learned from our cases that it is a common challenge to achieve complementarity between the human and AI agents in the work system by defining appropriate tasks and sub-processes for each agent (*C9*). Thus, this challenge is related to the *participants* and their respective roles in the *processes and activities* of the work system. Regarding this challenge, IP4 explained that it includes human agents' being concerned that current AI agents may cause more work than getting work done: "*Nevertheless, if we are now talking about using such an AI system, also to generate knowledge and so on... people are indeed worried at the moment that they actually have more work than before.*"

Good Practices of Human-AI Hybrid Execution

No.	Description	Stakeholder	Relation to WST research model	Source
P7	Ensure mental models of all involved agents (human and AI agents) along the human-AI hybrid lifecycle are aligned	Tech. implementer, Org. implementer	Participants	Case A, Case B, Case D
P8	Train AI-specific competences of human agents to ensure collaborative human-AI hybrids (e.g., prompting, critical assessment of interaction)	Org. implementer	Participants, Strategies	Case A, Case B
P9	Create a code-free communication interface for human-AI hybrids to enable seamless collaboration between humans and AI agents (e.g., conversational AI)	Tech. implementer	Participants, Technologies	Case A, Case B, Case C, Case D

Table 5. Identified Good Practices of Human-AI Hybrid Execution

Next to four challenges, we identified four good practices for human-AI hybrid execution from our multiple case study. For human-AI hybrid execution, it is crucial to ensure that the mental models of all involved agents (human and AI) are aligned throughout the lifecycle (*P7*). As an example, the technical implementer must understand the “mental model” of the algorithm and at the same time teach the AI system the mental model of the end-users to ensure alignment between these two agents. Our cases A, B, and D demonstrate this good practice, where interviewees explained to us that clear definitions of each agent's role and responsibilities ensured alignment of mental models of human and AI agents. Therefore, we relate this practice to the human and AI *participants* of the work system.

Further, when integrating AI agents into workflows, it is essential to train human agents with AI-specific competencies (*P8*). The organizational implementers in cases A and B demonstrated this practice, by ensuring human agents were trained in competencies such as prompting and critically evaluating AI-generated work results. This practice therefore relates to the *participants* of the work system and the overall organizational *strategy*. IP3 emphasized the importance of training AI-literate human agents who can effectively collaborate with AI agents: "*Then of course [...] employee training is certainly also a possibility. We've often done this in the past to show people how it works, what the options are, what works and what doesn't. I think a combination of all these things is important, because otherwise questions [i.e., prompts] are asked that don't fit the technical implementation and then [...] cause unnecessary frustration [...]*". Finally, the creation of a code-free communication interface for human-AI hybrids was observed out of the case documents as a practice to enable seamless collaboration between humans and AI agents (*P9*). E.g., the technical implementer developed innovative solutions to facilitate intuitive interactions with conversational AI models in case B, making it easy for non-AI experts to collaborate. Similarly, in cases C and D, the technical implementer's interface enhancements enabled human-AI hybrid teams to work efficiently together. In these cases, there was not only a conversational design but also filtering applications, well known from tools like Excel. Overall, these code-free interface empowered humans, especially non-AI-experts, and AI systems to work harmoniously, driving successful decision-making. Therefore, we relate this practice to the collaboration of the *participants* and the *technologies* in the work system.

Again, similarly to the practices identified for the construction phase of human-AI hybrids, the practice *P8* also seems applicable to non-AI initiatives, as training employees to work with new technologies is equally important in cases of other digital technologies. However, again we see that this practice remains crucial in the AI context.

Discussion

As raised in previous research (Fabri et al., 2023), our study aimed to contribute to understanding challenges and good practices regarding human-AI hybrids by looking at the phases of the human-AI hybrid lifecycle based on the WST: construction and execution. In line with the socio-technical nature of the WST, we identified two distinct roles that play crucial parts but also face unique challenges during the construction and execution of human-AI hybrids: the organizational implementer and the technical implementer. For each of these roles, we identified several challenges and good practices along the lifecycle of a human-AI hybrid that relate to different aspects of our WST-based conceptualization of human-AI hybrids. Furthermore, we conducted an exhaustive analysis of the relevant WST elements (*environment*, *strategies*, *infrastructure*, *processes and activities*, *information*, *technologies* and *participants*) to identify the specific challenges and good practices regarding these elements that arise during the construction and execution phases of human-AI hybrids.

Importance of a Socio-Technical Perspective on Human-AI Hybrids

Our study reveals that both technical and organizational implementer perspectives played a comparable role in the construction and execution of AI systems throughout their lifecycle. This finding corroborates previous research highlighting the importance of integrating technical and social aspects in the construction and execution of building human-AI hybrids (Hemmer et al., 2021; Raftopoulos and Hamari, 2023). By incorporating both stakeholder perspectives, organizations may be able to better navigate the complexities inherent in human-AI collaboration, ultimately enhancing their chances of success. Furthermore, the importance of both stakeholders across the lifecycle of building human-AI hybrids indicates that the underlying research model of the socio-technical work system theory fits into the study design.

Structuring the Design of Human-AI Hybrids Along the Work System Lifecycle

Our findings reveal that the **construction phase** of the human-AI hybrid lifecycle is characterized by a focus on the architectural aspects of the human-AI hybrid work system, like *infrastructure*, *environment*, *technologies*, and *strategies*. For instance, challenges such as dealing with data issues (*C4*) or algorithm specifics (*C5*), lack of expertise in AI technologies (*C2*), and organizations focusing too much on AI technology trends rather than understanding the use case and underlying process (*C3*) all highlight the importance of setting up a strong architectural foundation for the human-AI hybrid. Similarly, good practices such as building a project setting to quickly test different use cases of human-AI hybrids in an organization to evaluate potential usefulness (*P1*), defining quality gates for subprocesses and decisions carried out by AI agents (*P2*), and conducting business process analysis to identify appropriate human-AI hybrid use case(s) (*P4*) all demonstrate the importance of careful planning and setup in this phase. By focusing on these architectural aspects, we can better understand how to design and implement effective human-AI hybrids that are well-suited for their specific contexts and goals.

For the **execution phase**, the findings highlight the importance of considering the *participants*, i.e., human and AI agents, involved in the human-AI hybrid work system. In fact, all challenges and good practices relate to the element *participant* of the WST, underscoring the significance of their composition and collaboration in this phase (Swan and Worall, 1974). For the execution phase, the findings highlight the importance of considering the *participants*, i.e., human and AI agents, involved in the human-AI hybrid work system. In fact, all challenges and good practices relate to the element *participant* of the WST, underscoring the significance of their composition and collaboration in this phase (Swan and Worall 1974). This suggests that effective execution of a human-AI hybrid requires careful consideration of how human and AI agents interact with each other, including their skills, roles, and expectations. For instance, our findings emphasize the need for training AI-specific competences among human agents (*P8*) and creating a code-free communication interface to enable seamless collaboration between humans and AI agents (*P9*). Moreover, challenges such as reaching appropriate reliance of human agents on AI agents (*C7*) and achieving complementarity in process execution by defining appropriate subtasks and processes for each agent (*C9*) also highlight the importance of participant interaction. By focusing on the participants and their collaborative dynamics, we can better understand how to design and implement effective human-AI hybrids that leverage the strengths of both human and AI agents. In comparison, the construction and execution phases highlight a distinctly different focus between each other. The construction phase is characterized by a strong focus on *architectural design*, while in the execution phase, the majority of challenges and good practices revolve around the *participants* involved in the work system, emphasizing the importance of their composition, collaboration, and skills. This shift in focus underscores the crucial role that architectural design plays in enabling successful human-AI collaboration and the focus on participants in executing the human AI hybrid.

Finally, regarding **both phases of the human-AI hybrid lifecycle**, the integration of AI systems into organizational processes presents several unique challenges and opportunities. For instance, our study highlights the importance of acknowledging AI's autonomous capabilities in both the development and testing phases. This blurs traditional software engineering phases, necessitating a more fluid approach. Moreover, AI systems are not mere tools but active participants who learn from their environment and adapt to new situations. As IP7 notes, AI is a new stakeholder in the testing process, emphasizing the need for organizations to rethink their testing strategies. Similarly, IP3 observation that software engineering steps are converging underscores the importance of considering AI as an integral part of the development process. In light of these findings, we emphasize that research models such as the WST respect the emergence of AI as autonomous agents. No longer can participants simply be viewed as human actors; instead, we must consider AI systems as co-equal entities that require deliberate consideration in organizational construction and execution. Thus, we hypothesize that the combination of an architectural focus during the construction phase and a focus on participants – of which the AI itself becomes a part of – during the execution phase may be specific to human-AI hybrids and may differ from cases focusing on other, non-AI technologies.

Theoretical Implications

Our study makes several theoretical contributions and yields interesting directions for future research. First, our empirical insights into challenges and good practices regarding the construction and execution of human-AI hybrids represent an important contribution to the existing theoretical framework that seek to structure the design space of human-AI collaboration and human-AI hybrids (e.g., Braun et al. (2023), Jakob et al. (2024)). Together with the design dimensions identified in these frameworks, future research may use our results to develop a systematic method to implement human-AI hybrids in organizations, e.g., following the design science paradigm (Peffers et al., 2007). Second, our finding that the work system's *participants* are a particular focus during the execution phase of human-AI hybrids makes us curious as to whether, in an ideal situation, *participants* should also play a more prominent role in the construction phase. Especially if we want more human-centered AI to be built in the future with the goal of complementarity (Auernhammer, 2020; Hemmer et al., 2021; Shneiderman, 2022), future research should investigate how the *participants* and their respective concerns can be reflected over the entire lifecycle of constructing and executing human-AI hybrids. This may also imply training AI competencies of employees during hybrid construction as described by Gimpel et al. (2024), as with the increasing interaction of human and AI agents competencies of humans will need to adapt to further ensure complementarity (Gimpel et al., 2024). Third, achieving complementarity in process execution by defining appropriate subtasks and -processes for each agent (*C9*) is a challenge that not only we identified but should be the goal of constructing human-AI hybrids (Donahue et al., 2022; Hemmer et al., 2024; Holstein et al., 2023). Furthermore, the challenge of reaching appropriate reliance of human and AI agents seems to be crucial in our study, just like in others (Benda et al., 2022; He and Gadiraju, 2022; Hemmer et al., 2024). This congruence between the empirical findings of this investigation and previous research demonstrates a high level of generalizability, thereby substantiating the internal validity of these results (Eisenhardt, 1989).

Managerial Implications

The findings of this study offer several managerial implications for organizations seeking to construct and execute human-AI hybrid systems. Firstly, it is essential to prioritize the development of AI-specific competencies among human agents, ensuring seamless collaboration with AI systems (*C2, P8*). Secondly, companies should adopt a more fluid approach to software engineering phases, blurring traditional boundaries between development and testing (*C8*). Moreover, organizations must acknowledge the autonomous capabilities of AI systems and integrate them as active participants in the development process (*P2, C6*). Finally, embracing a socio-technical perspective that encompasses both technical and organizational aspects is crucial for successful human-AI hybrid implementation (see relation to work system theory). By adopting these strategies, companies can better navigate the challenges inherent in AI-driven innovation and create effective human-AI hybrids that drive business value.

Limitations and Suggestions for Future Research

Besides our best efforts, this study also comes with some limitations. First, as documented in challenges C1 and C2, there are currently few experts with the required expertise in setting up human-AI hybrids who can be involved in the early stages of construction, making it challenging for organizations to systematically approach the human-AI hybrid implementation. However, these challenges may only be of temporary nature, as AI technologies will likely continue to spread and increase in usage, allowing more individuals to become familiar with AI technologies. Thus, we hypothesize that we will see a growth in experts who can be involved in the early stages of development in the future, automatically alleviating these challenges as a side effect. Second, as described above, all our selected cases were deemed a successful implementation of human-AI hybrids. Our study therefore may contain some form of survivorship bias (Elton et al., 1996). This may have affected the responses of our interviewees and the collected data due to a positive perception of the sampled cases. Thus, in future research building on this conference paper, we seek to also investigate the challenges that were faced by cases of human-AI hybrid implementation that failed. Third, we also encourage future research to study additional cases to generate complementary insights for further areas of the enterprise value chain (Porter, 1991). By mapping the identified challenges and practices to the different areas of the enterprise value chain, organizations would be enabled to easily identify relevant challenges and practices for a specific use case they seek to build a human-AI hybrid for. Finally, we also believe that some of the identified challenges and practices may be related to each other (i.e., some of the identified practices may address certain challenges). Therefore, we deem it promising for future research to investigate the relationships between the challenges and practices quantitatively.

Conclusion

With this study, we set out to bridge the gap between existing theoretical frameworks that structure the design space for human-AI hybrid implementation and practical insights from existing implementations of human-AI hybrids. We conducted a multiple case study of four cases that successfully implemented a human-AI hybrid in a live, productive organizational setting and documented nine challenges as well as nine good practices for the constructing and executing phases of human-AI hybrids. Further, we found that during both phases, a technical and an organizational perspective must be simultaneously considered. Thus, the challenges and good practices relate to the roles of the technical and organizational implementer in the human-AI hybrid construction and execution. Our results reveal that during construction successful implementations focus on the architecture of the human-AI hybrid (i.e., aspects such as the used *infrastructure*, *technologies*, and the overall organizational *strategy*), whereas during execution the focus shifts towards the *participants* (both human and AI agents) of the human-AI hybrid and their collaboration on the joint task or process. Based on the findings, we highlighted several theoretical and practical implications and opportunities for future research.

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