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Designing and Managing Human-AI Interactions

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A plethora of submissions to this Special Issue showed that while AI is increasingly being embedded in information systems with potentially severe consequences for humans, including medical diagnostics (McKinney et al., 2020), floorplan design (Khang, 2021), job recruitment (Dastin, 2018), art (Ramesh et al., 2022), credit scoring (Wang et al., 2019), and autonomous vehicles (Grigorescu et al., 2019), the social aspects of interactions between humans and AI systems remain under-researched. This is surprising given IS's rich tradition as a discipline in theorizing and studying both the technical elements as well as the human aspects in designing and managing complex systems (Beydoun et al., 2019; Dwivedi et al., 2015).

Artificial Intelligence (AI), described as non-human intelligence that is flexible and autonomous enough to understand and learn from data to achieve specific outcomes (Kaplan & Haenlein, 2019), has reached—and even surpassed—the ability of humans in multiple domains (Arrieta et al., 2020; Sugumaran et al., 2017). While different definitions exist, there is a general understanding that AI includes learning, reasoning, and adapting capabilities as key features.

Studying the interaction between human and AI necessitates researchers and practitioners to go beyond smart algorithms. In fact, a successful implementation requires—apart from effective coordination, complex problem-solving skills and teamwork—a shared understanding of the human agency and that of the AI system (Seeber et al., 2020). While a shared understanding is a key step towards facilitating a link between both (Arrieta et al., 2020; Kaplan & Haenlein, 2019), it will also require new approaches for conceptualization (Bittner and Leimeister, 2014).

Adding the mounting concern about privacy, security, and transparency of AI systems, it is therefore not surprising that scholars in IS, human–computer interaction, and related disciplines have called for more research to reconcile these tensions between AI agency and human agency (Abedin, 2021). As AI gets more autonomous and takes on more agency, AI-human interactions become ever more determined by algorithms (Sundar, 2020). A study about organizational decision-making, for example, argued that the actual AI effects on decisions are the results of unpredictable individual and organizational learning processes and are therefore non-deterministic (Seidel et al., 2018). While AI may take over human decision-making for routine and structured tasks, it is impractical—if if not infeasible—to assume that AI will take over in professional contexts. Problem complexity, human factors, decision accountability, context ambiguity, and decisional uncertainty are too incumbent with the current state of AI.

At the onset of our call for the Special Issue, we were driven by the observation that despite an increasing interest in the human-AI interaction space, there was a need for more theory and research geared towards providing a richer conceptualization about the human experience of AI use for various settings and from both technical and non-technical perspectives. Based our own study of the human-AI interaction literature at the time, we proposed an organizing framework that summarized key challenges and mitigation

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considerations in designing and managing human-AI interactions. Interestingly, once the set of articles for the Special Issue were finalized, we noticed that we were able to map each paper into our framework, as later demonstrated.

1 A Framework for Organizing Future Research on Human-AI Interactions

The framework contained four research challenges across two levels of considerations (i.e., design and management). The framework, as per below and Table 1, gives rise to four challenges: AI user interface design, Human-AI conversations and collaboration, explainability, accountability, fairness and bias, and lastly AI agency and human-interaction with agentic AI.

1.1 AI User Interface Design

With the increasing diffusion and capacity of complex algorithms, there is a need to better understand how AI interfaces should be designed to be able to effectively use and control the system (Amershi et al., 2019). This need is rooted in AI's complexity and functional capability, its many shapes and forms (e.g., AI-based decision support systems vs. AI-based robotics), and the varying levels of user expertise required (e.g., laymen vs. domain expert vs. AI engineer). While the intention is to make AI systems' user interfaces more effective and easier to use, perceptions about the unreliability of AI and that its interface is merely cosmetic has created disagreements about how to design guidelines and principles for AI user interface alternatives. Extending our design knowledge, for example, in the form of design principles and theories, is a must (Benda et al., 2022).

1.2 Human-AI Conversations and Collaboration

Today's AI is increasingly capable of processing natural language in written and spoken form. For example, language models, like GPT-3 from OpenAI (www.openai.com), are used for understanding and generating natural language texts as part of human-AI conversations, as well as for generating articles on any given topic. This allows for new possibilities for technology use and control. However, these developments also require that we carefully investigate how known pitfalls of human-to-human communication (e.g., double negatives, sarcasm) may apply to human-AI-communication, as well as how to avoid consequent misunderstandings (Arrieta et al., 2020). Communication between human and AI also allows for new means of collaboration, leading to settings of "hybrid intelligence" (van der Aalst, 2021). To maximize the usefulness of AI in human-AI-settings, it is hence necessary to investigate how communication influences human-AI-collaboration, and how the latter deviates from conventional human–human-collaboration (Amershi et al., 2019). In addition, researchers need to understand the multifaceted options of human-AI-collaboration, as they will change how tasks are carried out and hence influence the future of work in general.

1.3 Explainability and Accountability, Fairness and Bias

Advances in hardware (i.e., computing power) and software (i.e., complex machine learning algorithms) have led to today's powerful and often autonomous AI systems. But due to its complexity, AI is often viewed as a black box (Meske et al., 2022). This is problematic as AI systems have been increasingly used in situations with potentially major consequences for human life (Meske et al., 2022). For that reason, questions related to accountability need to be addressed, and AI models need to be explainable and their chain of reasoning leading to an outcome need to be reproducible. One problem is that instruments of explainable AI, or interpretable machine learning techniques, are often developed by computer scientists for computer scientists (Abedin, 2021; Arrieta et al., 2020); in contrast, we argue that research on explainability needs to focus more on end-users who require different, and more approachable, forms of explanations.

Another problem is that complex AI systems tend to be developed as a composition of multiple software components, APIs, and libraries, each of which has different interaction and reporting mechanisms that were designed in isolation. Integrating different logging and reporting information into a coherent narrative for end-users is a formidable challenge. In addition, questions of explainability and accountability need to be answered for different stakeholders (e.g., regulators, developers, managers, users) along with the process of AI design and management.

1.4 AI Agency and Human Interaction with Agentic AI

As advances in AI algorithms and systems provide proxy agency to users through customization of tasks and decision, they become increasingly capable of exerting their own agency (Sundar, 2020), which in turn gives rise to the tension between machine agency and human agency (Abedin, 2021). There are different research streams on agency, many of which discuss agency only as a potential attribute of humans (e.g., Nevo et al., 2018). We argue that because of AI's increasing capability to autonomously carry out tasks, AI should increasingly be viewed as a potential "team member." Research needs to further investigate the extent to which AI can have or develop agency itself. This notion of agentic AI raises questions on how changes in the

Table 1 Human-AI interaction challenges and mitigation considerations

Human-AI interaction challenges	Mitigation considerations	
	Design	Manage
AI User Interface Design	- Which challenges come with AI technology regarding the design of user interfaces and hence various modes of human-AI interaction? - How do interfaces need to be designed in order to increase trust and technology acceptance?	- What can (IT) management learn from how the interface of AI is used (e.g., which features)? - Which role does the user interface play in managing human-AI interaction?
Human-AI Conversations and Collaboration	- How should communication between AI and humans be designed in order to avoid misunderstandings on both ends? - How can AI be designed in order for it to adapt to individual characteristics of humans?	- How should the collaborative interplay between humans and AI be orchestrated in order to harness the potential of hybrid intelligence? - How can information exchange in human-AI interaction be documented and used to foster organizational knowledge management?
Explainability, Accountability, ethics, fairness and bias	- How can explainability be designed into the process from AI development by experts (e.g., engineers) to AI usage by laymen? - To which extend may we need to expand or re-think the term 'explainability' in the context human-AI interaction? - What are AI system design consideration for accountability, ethics, fairness and bias of AI systems in operation in human society?	- How should AI governance be implemented in organizations in order to supervise human-AI interaction and to allocate responsibility as well as accountability? - How does explainability influence the possibility to manage and AI? - What processes are needed in AI governance to deal with accountability, ethics, fairness and bias issues in decisions or recommendations made by AI?
AI Agency and Human Interaction with Agentic AI	- To which degree can and should agency be designed into AI? - How does the notion of agentic AI influence the design of human-AI interaction?	- How does the management of agentic AI differ from the management of human agents? - How can management resolve and react to potential conflicts between agentic AI and humans?

allocation of agency may influence the modes of agent and agentic interaction.

2 The Special Issue

We are delighted to introduce our Special Issue on "Designing and Managing Human-AI Interactions." Our initial call was announced in June 2022 via the Association for Information Systems (AIS). Subsequently, Information Systems Frontiers sponsored our inaugural mini-track on "Explainable Artificial Intelligence (XAI)" at the 54th Hawaiian International Conference on Systems Science (HICSS) from which papers were invited to submit extended manuscripts for this Special Issue.

Our intention was to highlight the need for conceptualizing and empirically studying the challenges associated with AI systems. We aimed to explore, theorize, and test guidelines for upholding and implementing good AI practices with regards to individual, group/team, organizational, and societal level of analysis, and across a variety of domains. We solicited case studies, surveys, and experiments, as well as qualitative, design science, and collaborative action research studies.

Our target audience with the Special Issue were academics, executives, and policy makers who could illustrate innovative approaches, resolutions, and solutions to the described tensions, risks, and opportunities. We especially sought papers that offered theoretical models along with observations or evidence of consequences related to these models.

Overall, our call yielded 26 submissions. Submissions were screened for fit by the Special Issue guest editors which led to three initial desk rejections. The remaining papers were sent out for review to at least two reviewers. After more than two rounds of revisions, ten papers were accepted for publication.

Using our initial framework as a guide, we were able to map each of the articles onto the four challenges as per Table 1. In the following, we will summarize key findings of articles.

2.1 Challenge 1: AI User Interface Design

Elshan et al. (2022) conduct a study entitled "*Understanding the Design Elements Affecting User Acceptance of Intelligent Agents: Past, Present and Future* " and present a systematic literature review of intelligent agents by studying the design elements affecting user acceptance. Intelligent agents are described as agents that perceive and respond in a timely manner and are capable of interacting with other agents (i.e., humans) and react to their environment. The review analyzes 107 Information Systems and Human–Computer Interaction papers and identifies 389 relationships between design elements and user acceptance of intelligent agents. These relationships are grouped under five design elements (interaction, visual, verbal, auditory, and invisible) and three key dimensions (relational elements, social elements, and functional elements). The authors then present a research agenda for each design element under each of the three intelligence agents' dimensions.

2.2 Challenge 2: Human-AI Conversations and Collaboration

In the paper entitled *"Organizational Learning for Intelligence Amplification Adoption: Lessons from a Clinical Decision Support System Adoption Project,"* Wijnhoven (2022) studies intelligence amplification as a mechanism that aims at making humans smarter with the use of artificial intelligence (AI). As part of this mechanism, AI indirectly effects actual human decisions by keeping the human in the loop of AI. Studying a clinical decision support system, the paper examines the adoption challenges of intelligence amplification systems and presents challenges in the socialization, externalization, combination, and internalization stages of intelligence amplification adoption. The author finds that many of the reasons for not trusting AI systems are not technical or psychological in nature but related to ethical, legal, and managerial intelligence amplification requirements that are insufficiently met. Managers need to promote specific capabilities, including personal skills and emergent organizational and inter-organizational capabilities, to address these challenges.

In their paper entitled *"Collaborating with Virtual Assistants in Organizations: Analyzing Social Loafing Tendencies and Responsibility Attribution,"* Stieglitz et al. (2022) examine the collaborating with virtual assistants (VA) in organizations and analyze social loafing tendencies and responsibility attribution. In particular, they aim at understanding the effect of VAs on virtual teams and whether employees show social loafing tendencies, i.e., applying less effort for collective tasks when compared to working alone. Through an online experiment study, the research finds that social loafing tendencies in virtual collaboration are present and that participants tend to cede responsibility to the VA. The authors develop a new construct of smart loafing, which represents the purposeful reduction of the individual effort in human-VA collaboration to save cognitive resources for enhancing efficiency at work. The research concludes that while smart loafing may not lead to lower team performance in some organizational contexts, it may be not "smart" in some other contexts, such as learning environments.

In their paper *"Design and Evaluation of a Conversational Agent for Facilitating Idea Generation in Organizational Innovation Processes,"* the authors Poser et al.

(2022) address the challenge of large numbers of incomplete, unclear, and unspecific submissions on idea platforms, which often hinder organizations to exploit the full potential of open innovation initiatives. As part of a design science research project, the authors design a conversational agent (CA) to aid contributors in generating elaborate ideas for idea platforms where human-mediated facilitation is not scalable. The study derives prescriptive design knowledge in the form of design principles, as well as instantiates and evaluates the CA in two successive evaluation episodes. The design principles contribute to the current research stream on automated facilitation and can guide providers of idea platforms to enhance idea generation and subsequent idea selection processes. Results indicate that CA-based facilitation is engaging for contributors and yields well-structured and elaborated ideas.

In their paper *"'Don't neglect the user!' – Identifying Types of Human-Chatbot Interactions and their Associated Characteristics,"* the authors Nguyen et al. (2022) focus on human interaction with conversational agents (CAs). While research on human-CA interactions provides insights into the role of CAs, the active role of users has been mostly neglected. The authors address this void by applying a thematic analysis approach and examine 1,000 interactions between a chatbot and customers of an energy provider. Informed by the concepts of social presence and social cues and using the abductive logic, they identify six human-chatbot interaction types that differ according to salient characteristics, including direction, social presence, social cues of customers and the chatbot, and customer effort. The authors find that bi-directionality, a medium degree of social presence and selected social cues used by the chatbot and customers, are associated with desirable outcomes in which customers mostly obtain requested information. The findings help understand the nature of human-CA interactions in a customer service context and inform the design and evaluation of CAs.

In their paper titled *"Voice Assistant vs. Chatbot – Examining the Fit Between Conversational Agents' Interaction Modalities and Information Search Tasks,"* the authors Rzepka et al. (2022) focus on voice assistants (VAs) that offer speech as a new interaction modality. Compared to text-based interaction, speech is natural and intuitive, which is why VAs are commonly used in customer service. Drawing on task-technology fit theory, the authors present a research model to examine the applicability of VAs to different tasks. They conduct a laboratory experiment with 116 participants that completed an information search task with either a VA or a chatbot. Findings indicate that speech exhibits higher perceived efficiency, lower cognitive effort, higher enjoyment, and higher service satisfaction than text-based interaction. The authors also find that these effects depend on a task's goal-directedness.

2.3 Challenge 3: Explainability and Accountability, fairness and bias

In their paper *"AI decision making with dignity? Contrasting workers' justice perceptions of human and AI decision making in a human resource management context,"* Bankins et al. (2022) examine fairness of AI decision-making in a human resource management context and aim at understanding how fair employees perceive these decisions to be and whether they experience respectful treatment (i.e. interactional justice). This paper adds to the literature about procedural (i.e., how fair and reasonable the procedures to make a decision are) and distributive (i.e., how fair the outcomes of a decision are, such as resource allocation) forms of justice. Through an experimental survey study with open-ended qualitative questions, the author examine decision-making in six HRM functions and manipulate the decision-maker (AI or human) and decision valence (positive or negative) to determine their impact on individuals' experiences of interactional justice, trust, dehumanization, and perceptions of decision-maker role appropriateness. Findings indicate that the use of human decision makers over AI generally resulted in better perceptions of respectful treatment and that people experiencing positive over negative decision valence generally resulted in better perceptions of respectful treatment. In instances where these cases conflict people prefer positive AI decisions over negative human decisions.

In their paper *"Designing Transparency for Effective Human-AI Collaboration,"* drawing on the 3-Gap framework, the authors Vössing et al. (2022) study agent transparency as a means to reduce the information asymmetry between humans and the AI. According to the authors, there is a lack of consolidated design guidelines for information systems facilitating the collaboration between humans and AI systems. Following the Design Science Research paradigm, the authors formulate testable propositions, derive design requirements, and synthesize design principles. Two design principles are instantiated as design features of an information system in the hospitality industry, and two case studies are conducted to evaluate the effects of agent transparency. Findings indicate that trust increases when the AI system provides information on its reasoning; it decreases when the AI system provides information on sources of uncertainty. Additionally, the paper observes that agent transparency improves task outcomes as it enhances the accuracy of judgmental forecast adjustments.

In their paper titled *"Paradoxical Tensions Related to AI-powered Evaluation Systems in Competitive Sports,"* the authors Mazurova et al. (2022) investigate judging in competitive sports which is prone to errors arising from the inherent limitations to humans' cognitive and sensorial capabilities and from various potential sources of bias that influence judges. Artistic gymnastics offers a case in point;

given the complexity of scoring and the ever-increasing speed of athletes' performance, systems powered by AI seem to promise benefits for the judging process and its outcomes. To characterize today's human judging process for artistic gymnastics and to compare it against an AI-powered system currently being introduced in this context, an in-depth case study is conducted that analyzes interview data from various stakeholder groups (i.e., judges, gymnasts, coaches, federations, technology providers, and fans). It unearths several paradoxical tensions accompanying AI-based evaluations, including AI-powered systems' accuracy, objectivity, explainability, relationship with artistry, interaction with humans, and consistency.

2.4 Challenge 4: AI Agency and Human Interaction with Agentic AI

Ahmad et al. (2022) conducted a study entitled *"Designing personality-adaptive conversational agents for mental health care"* and studied conversational agents and their interaction with human in a mental health context. These agents are software-based systems that interact with humans through natural language. Their study examines how these agents can live up to their full potential to adequately incorporate dynamic human behavior for providing responses tailored to users' personalities. Utilizing a design science research approach, the authors design personality-adaptive conversational agents (PACAs). They formulate six design principles for PACAs for the domain of mental health care, which are grouped in two categories. The first category includes: (i) Principle of Proactive Support, (ii) Principle of Competence, and (iii) Principle of Transparency; this category represents the foundation of PACA. The second category transforms a conversation agent into a PACA and includes three principles: (i) Principle of Social Role, (ii) Principle of Anthropomorphism, and (iii) Principle of Personality Adaptivity. They enable adaptation in the form of customization and personalization to user preferences, and therefore offer a more tailored service based on users' needs and personalities.

3 Conclusion and Ideas for Future Studies

This Special Issue aimed at highlighting the need for conceptualizing and empirically studying the challenges associated with AI systems with a particular focus on exploring, theorizing, and testing guidelines for upholding and implementing good AI practices with regards to human-AI interactions. We proposed an organizing framework that demonstrates four challenges in human-AI interactions. Interestingly, our analysis of the submissions to the Special Issue revealed a greater attention to two of those challenges, human-AI conversations and collaboration, as well as explainability, accountability, fairness and bias. Less attention received AI user interface design and AI agency and human-interaction with agentic AI.

We believe moving forward that scholars need to further theorize agentic AI, examine in what ways interactions with agentic AI would be similar or different from a non-agentic AI and information systems, and further study the implications and specifications of AI's user-interface design in interactions with humans. We believe that separate yet related attention needs to be paid to the design and management challenges and mitigation consideration of Human-AI interactions. Withing this scope, there many important and novel questions that scholars may explore. In Table 1, we present some thematic areas for proposed future research under the design and management considerations. While by no means not exhaustive, we nevertheless hope that our questions will aid guiding future research considerations.

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