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# Human Agency in AI Configurations Supporting Organizational Decision-making

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### Full research paper

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## Abstract

The integration of human intelligence with Artificial Intelligence (AI) is becoming increasingly essential for leveraging benefits in organizational decision-making. This necessitates to understand human-AI collaboration configurations for managing collaborative intelligence. However, existing literature on Human-AI collaboration lacks structure and is fragmented regarding what exactly human intelligence (HI) contributes to AI collaboration and how AI systems can be configured in the decision-making process. This paper undertakes an organizing literature review to consolidate insights from existing literature. We identify six types of human agency as involved in collaborative intelligence and synthesize the findings into six Human-AI collaborative configurations explained by a matrix framework. By illuminating the complexities of Human-AI collaboration, the framework sheds light on the need for a nuanced understanding of the imbricating roles of HI and AI in decision-making, with important implications for the design and implementation of AI systems for organizational decision-making.

**Keywords** (AI, Artificial Intelligence, Human-AI collaboration, Collaborative intelligence, Hybrid intelligence, Human-AI partnership, AI teammate).

# 1. Introduction

Artificial Intelligence (AI) is increasingly being infused into many organizational processes. Its disruptive potential has been amply stressed, in particular with regards to enhancing the performance of, or automating, key business decisions (Giraud et al. 2022). AI generally refers to the simulation of human intelligence (HI) in machines that are designed to mimic human cognitive functions to perform actions often (semi)autonomously (Craglia et al. 2018; Borges et al. 2021). AI used in organizations has seen rapid adoption since 2017, reporting a 50-60% uptake rate in the most recent industrial surveys (Chui et al. 2022). Whilst benefits of greater levels of AI adoption are seen with improved efficiency and productivity, introduction of AI technologies in organizations still comes with a range of challenges (Dwivedi et al. 2021).

One of the challenges facing AI is the discrepancy between the promised level of automation in decision-making and the actual outcomes (Borges et al. 2021; Dwivedi et al. 2021; Namvar et al. 2022). This underdelivered promise has led to doubts and criticisms surrounding the autonomy of AI systems (Dwivedi et al. 2021; Gomes et al. 2022). Therefore, a growing focus shift to human-AI collaboration is driving attention on how human agency, how humans can purposefully utilize the provided technologies to fulfill their goals and needs (Leonardi 2011), can leverage AI capabilities (Lichtenthaler, 2018). In such a collaboration, humans are able to provide control and feedback to multiple points in the decision procedure and take actions facilitated by AI (Grønsund & Aanestad, 2020; Meske et al., 2022). This collaborative agency combines both human intelligence (HI) and AI, integrating AI advantages into social fabrics of an organization (Rai et al., 2019; Akata et al., 2020).

However, research on human-AI collaboration for decision-making in organizations has just emerged, presenting inconsistencies in defining such social-technical phenomenon and fragmentations in the discourse across boundaries involving IS, CS, Engineering and so on (Berente et al. 2021; Dwivedi et al. 2021; Gomes et al. 2022; Herrmann and Pfeiffer 2022), which led to confusion about what constitutes human-AI collaboration and how humans can effectively participate in automated decision processes. For example, there is no unified understanding of the concept of “AI” (Berente et al. 2021). Specifically, the concept of human-AI "collaboration" in the literature is ill-defined, which leaves many similar terms, such as "collaborative intelligence", "human-AI collaboration", “conjoined intelligence”, "human-in-the-loop", “hybrid decision” or “human-centered AI” vague and ambiguous.

Against this backdrop, this review paper advances understanding of human-AI collaboration for decision-making in organizations by consolidating insights from existing literature. Our organizing literature review (Leidner 2018) identifies the types of human agency involved in this collaboration through a hermeneutic approach (Boell and Cecez-Kecmanovic 2014). We synthesize our findings into six collaborative configurations and derive an overarching matrix framework, with the aim of facilitating future research and knowledge advancement in human-AI collaboration (Alvesson and Sandberg 2020).

Our paper contributes to a foundational understanding for achieving conceptual clarity on human-AI collaboration by identifying diverse patterns of how humans become integrated into the decision make processes. By incorporating the dimensions of control and feedback into our HI-AI framework, we offer a means to understand human roles that align with diverse types of collaboration configurations, highlighting agency and constraints. Moreover, our configuration framework focuses on a social-technical level for organizational decision-making contexts, which provides valuable insight into risks associated with their Human-AI collaborative configurations. Organizations can thus leverage this knowledge to formulate corresponding risk mitigation strategies. Finally, our overarching HI-AI collaboration matrix framework assists IS researchers by systematizing potential empirical settings of organizational AI adoptions and therefore can help AI researchers to select their case studies based on a typological understanding.

# 2. Background

AI in organizational settings has widespread uses, with significant adoption in domains such as manufacturing, medical practices, and supply chain management (Nimmy et al. 2022); whereas its application in other domains is still in a preliminary stage, such as financial investments and human resources management (Duan et al. 2019). Traditional AIs, or expert systems, are designed with pre-programmed rules by domain experts, whereas the contemporary conception of AI leverages its capacity to learn from data and past behaviors (Borges et al. 2021). Therefore, AI has advanced from standardized rule-based models to continuously strengthened learning approaches (Berente et al. 2021), which enables interactive human feedback for iterative improvements (Benbya et al. 2021; Gomes et al. 2022; Islas-Cota et al. 2022).

AI is not a new idea. The term was coined almost 70 years ago, with the original idea of teaching machines to think and reason like humans (McCarthy 1955). Since then the field has evolved, and today AI refers to a range of different ideas making AI a continually evolving field (Berente et al. 2021). Integration with AI creates new requirements for organizations to review and evolve organizational practices in decision-making (Herrmann and Pfeiffer 2022) and organizational learning management (Balasubramanian et al. 2022), in order to realize the complementary strengths from AI (Dilsizian and Siegel 2014). The new demands therefore seek to reflectively shape an organization's AI-related activities, which necessitate research into organizational AI adoption and evidence-based modalities for decision-making (Berente et al. 2021). As AI adoption for organizational decision-making is a socio-technical phenomenon (Sarker et al., 2019), a particular role falls to humans in configuring organizational resources, information, and processes.

Although AI is seen with a greater level of autonomy for making decisions and taking actions, and a plethora of studies have been devoted to developing new models that drive higher autonomous abilities (Borges et al. 2021), current research finds no empirical evidence for the effectiveness of automation of decision-making (Borges et al. 2021; Dwivedi et al. 2021; Namvar et al. 2022), highlighting the constraints and challenges for AI control when moving towards autonomy (Kumar 2017; Dwivedi et al. 2021). Consequently, research in IS has identified several technological limitations including: low interpretability in complex decision-making context (Shrestha et al. 2019), constrained transferability of knowledge to decision support systems (Sturm et al. 2021), vulnerable integrity through polluted data, mismanagement of adversarial attacks (Li and Chai 2022), misalignment of models against organizational process structure (van den Broek et al. 2021), as well as ethical challenges such as data-induced unfairness (Teodorescu et al. 2021), employee deskilling issues (Lebovitz et al. 2021) and decision failures due to lack of explainability (Bauer et al. 2021; Astiani et al. 2021; Jussupow et al. 2021). Hence, an increasing number of studies are shifting towards augmentation-focused uses of AI, which highlights the role of human agency in decision-making control.

Therefore, research into human-AI collaboration homes in on the role of human agency in leveraging AI affordances, investigating the optimal balance of human-AI control in AI implementations (Lichtenthaler 2018). Humans delegate agency to AI systems, but retain certain other processes to achieve an enhanced "conjoined agency" in decision-making (Murray et al. 2021). As such, humans are able to exert control and provide feedback at multiple points in the decision process, as well as taking actions facilitated by AI (Burr et al. 2018; Grønsund and Aanestad 2020; Meske et al. 2022). This collaborative agency combines both human intelligence (HI) and AI, integrating AI advantages into social fabrics of an organization (Rai et al. 2019; Akata et al. 2020).

Many similar terms to describe human-AI collaboration have been coined to apply both to the process of algorithm model design (Holzinger et al. 2019) and the actual decision-making uses of AI (Rai et al. 2019; Akata et al. 2020; Grønsund and Aanestad 2020). Yet, the configurations of agency distributed between human and AI are frequently seen at either end of the human–AI spectrum in practical studies (Arnott et al. 2017; Lichtenthaler 2018; Namvar et al. 2022). While human interaction and AI automation is not mutually exclusive (Benbya et al. 2021), the understanding on how human and AI can intentionally assist, complement, and substitute each other in organizational decision-making processes still lacks systematic understanding (Makarius et al. 2020; Murray et al. 2021; Giraud et al. 2022). Hence, this review paper asks the following questions: (1) What types of human agency are described in the literature on the use of AI to support decision-making? (2) How is human-AI collaboration in decision-making studied in the current literature? (3) How are the identified human-AI collaboration configurations related to each other? Our findings contribute by outlining socio-technical configurations, offering opportunities to rethink the complex HI-AI partnership with a focus on control and feedback in organizational decision-making processes (Benbya et al. 2021; Teodorescu et al. 2021).

# 3. Research Approach

To explore the types of agency and configurations related to organizational decision-making in the AI and IS literature, we conducted an organizing literature review (Leidner 2018) following the hermeneutic approach developed by Boell and Cecez-Kecmanovic (2014). Since the aim of this paper is to classify, compare and map relevant theories in relation to HI-AI relationships (Boell and Cecez-Kecmanovic 2015), the hermeneutic approach provides us with reflexive interpretations, facilitating insightful understanding of the studied phenomenon, rather than reproducing or reinforcing pre-existing viewpoints (Alvesson and Sandberg 2020).

As such, we utilized an iterative search process with three rounds of the first "search and acquisition" hermeneutic circle to identify, construct, and connect articles with a rich and wide engagement (Boell and Cecez-Kecmanovic 2014). Following the hermeneutic approach, different research strategies with key search terms were gradually developed and conducted on the Scopus database. The Scopus database was selected due to its strong interdisciplinary nature and extensive coverage of over 21,950 journals (Iowa State University 2022), including 847 IS journals (Boell and Wang 2019). We performed 3 iterations to help us conceptualize human-AI collaboration as shown in Appendix A, growing from search terms including "AI", "Artificial intelligence", "Machine learning", "ML", "Deep learning", "Business intelligence", "Decision support", "Human agency", "Human-AI collaboration", "Collaborative agency", "Human-centered machine learning", "AI teammate", "Conjoined agency", "Human in the loop". We limited our sample to papers published after 2013 and left out papers that do not talk about human agency, do not provide clear indications of human roles in working with AI, purely focus on developing machine learning models, or are not related to organizational decision-making.

We terminated the search circle when a sufficient understanding of human-AI collaboration was reached, and further searches only retrieved publications that provide marginal new insights or setups of human-AI collaboration (Boell and Cecez-Kecmanovic 2014). In total we analyzed 72 articles; a full list of articles is provided in Appendix B. Our research goal went beyond the gathering and presentation of findings, instead aiming to synthesize the existing literature to develop a new perspective on the topic (Alvesson and Sandberg 2020; Webster and Watson 2002).

After collating articles and carefully reviewing their contents, all 72 articles were organized in Zotero and subjected to thorough examination. The team then assessed the types of human agency according to the levels of human controls over the decision-making outcome or process. One team member provided a textual summary highlighting the terms used to describe human agency in the AI partnerships, providing a note for each of the 72 articles. These summaries were then reviewed and discussed within the team to categorize the various types of human agency, which produced one or more tags related to each article. Disagreements were resolved by referring back to the original text, and the team either reached a consensus on the classification of a particular existing tag or introduced new categories of agency with a new tag. In total, we identified six distinct types of agency, which were fully tabulated by one team member as depicted in Appendix B, to facilitate further analysis of human-AI configurations. For each type of agency, we compiled the summarized descriptions and examined the collaboration patterns. One team member subsequently rendered the visual representations of the six identified configurations in a diagram, which were then verified and confirmed within the team. The finalized diagram is presented in Appendix C. This effort led to the final step, where we distilled our insights into a matrix framework to align with our research objectives.

# 4. Findings

Our study identified six types of human agency, which we critically assessed to identify any contradictions or missing explanations (Boell and Cecez-Kecmanovic 2014) in the existing literature of human-AI embedded decision-making applications. Our goal of reconceptualizing existing thinking triggers a new understanding of collaborative boundaries shared by human actors and AI systems (Alvesson and Sandberg 2020), which leads us to reevaluate and reconstruct the extant literature to answer our research objectives. The following three sections address our research questions in turn.

## 4.1 Human agency

Human agency in HI-AI collaboration commonly exhibits specific characteristics (Duan et al. 2019). We identified six overarching types of agency in the current literature (Table 1). Human agency displayed in extant studies can be seen related to the degree of responsibility that humans hold (Parent-Rocheleau and Parker 2022), AI algorithms characteristics (Holzinger 2016), and the nature of the decision and the task (Nahavandi 2017; Borges et al. 2021; Parent-Rocheleau and Parker 2022). The degree of responsibility relates closely to ethical imperatives that require humans to be accountable for their decisions, which should be beneficial to other human stakeholders (Jotterand and Bosco 2020; Tolmeijer et al. 2022) on fairness (Parent-Rocheleau and Parker 2022) or accuracy (Braithwaite 2020). This relationship requires human participation and control in decision making. For instance, the EU requires human intervention in every decision cycle of a system, even if the outcome can be fully automated (Enarsson et al. 2022).

Other studies characterize AI algorithms in a more technical manner, where the configuration of human involvement is determined by technology capabilities (Holzinger et al. 2019; Kordzadeh and Ghasemaghaei 2022). Traditional rule-based algorithms require greater human control, while more advanced machine learning shows higher learning capabilities to automate predictions and perform actions (Lee and Floridi 2021). For example, in supervised or semi-supervised ML, human technicians and field experts control labelling data and constructing algorithms. By contrast, unsupervised ML does not require human technicians to label data, but human experts and technicians collaborate to comprehend and check the algorithms learned from raw data (Holzinger 2016), where interactive ML requires human feedback to refine models (Newell and Marabelli 2015; Sturm et al. 2021). Hence, the adoption of different technologies will lead to diverse forms of human participation.

Furthermore, human agency also reflects the characteristics of the task and decision, as a decision process comprises a set of interlocked tasks that can be automated or monitored by either machines or humans (Borges et al. 2021; Fernández-Macías and Bisello 2022). The value-laden context attached to the decision will increase its complexity and will be harder for AI to understand and interpret. Thus, AI systems show different capabilities in structured and unstructured decisions (Duan et al. 2019), which leads to varied justifications of methods for the Human-AI intelligence balance (McBride 2021).

| Agency | Explanation |
|---|---|
| Verification | Humans check and comprehend decision outputs, to accomplish the decision derived from AI provided options. For instance, human actors utilize AI-integrated CRM systems for make-or-buy decisions while retaining the final decision-making authority (Ledro et al. 2022); a banker validates AI-screened loan approvals (Teodorescu et al. 2021); expert employees judge decision outputs to ensure validity (Asatiani et al. 2021). |
| Supervision | AI retains full decision autonomy, where humans have nominal control over the action. For instance, the use of AI expert systems to replace structured or semi-structured decisions (Duan et al. 2019); hiring managers rely on AI recommendations in recruiting process where human HRs have continuedly fed back to the model providing high clarities on hiring fairness objectives (Teodorescu et al. 2021). |
| Cooperation | AI automates task-based decisions to generate insights for humans, humans then use task-based outputs to complete the entire decision-making job. For instance, AI systems can augment learning and innovation for human experts in organizational knowledge management (Sturm et al. 2021); the co-development of AI systems with stakeholders (Weber et al. 2022); humans use people analytic software outputs to hire, forecast employee retention and training needs (Giermindl et al. 2022). |
| Intervention | Humans only intervene in the decision process when the decision output is perceived to be biased, inaccurate or inappropriate. For instance, human brokers remove racial discrimination in mortgage lending decisions (Lee and Floridi 2021); HR managers intervene to remove talent searching bias in people analytics systems (Giermindl et al. 2022); humans intervene in robotic surgery (Limerick et al. 2014). |
| Rejection | Humans have the right to opt out of an AI system in their decision loop when the system generated result is found to be unacceptable. For example, doctors ignore AI recommendations when being skeptical of medical AI (Rajpurkar et al. 2022); employees have opt-out right in using people analytics (Parent-Rocheleau and Parker 2022). |
| Regulation | Humans regulate the protocol for data inputs, the development of models and output standards for decision quality. For instance, AI learns ground truth standards from domain experts by feeding it with selected history data (van den Broek et al. 2021); human-driven data analysis for group decision-making (Fügener et al. 2021) and mutual learning (Berente et al. 2021). |

*Table 1. Six Types of Human Agency in Human-AI Collaboration*

## 4.2 HI-AI configurations

Based on the above identified types of human agency, we analyze current human-AI collaboration studies on how human agency is figured and reconfigured at the human-machine interface (Suchman 2007) in decision-making routines (Grønsund and Aanestad 2020). This emphasizes the active role of human actors in the human-AI team, who need to adapt to the level of autonomy of their AI agents (Hauptman et al. 2023), which manifests in distinct configurations.

Therefore, we further relate the six identified types of human agency to the associated control activities and algorithm characteristics, aiming to enhance clarity regarding collaborative configurations between human actors and AI systems to summarize how collaborative intelligence is modeled in organizational decision-making processes. For example, verification type agency involves higher human control capacities and is associated with less autonomous AI algorithms. In contrast, regulation type agency exhibits a lower level of human control and is related to stronger machine learning capabilities.

We integrate the six types of agency into six configurations to further show the interactions between HI and AI, as shown in Table 2, and explain each one individually in the following sections.

| Configuration | **Agency** | Example |
|---|---|---|
| 1 - AI Suggest, HI Decides | *Verification:* Humans are the final deciders; AI only provides recommendations for humans based on human-labeled knowledge or rule-based model. | • Medical diagnosis assistance systems (Jussupow et al. 2021);<br>• CRM decision-making systems (Vlačić et al. 2021). |
| 2 - HI Feedback, AI Optimizes | *Supervision:* Human continuously optimize AI systems by providing feedback; AI systems then improve accordingly to optimize the AI-led decision outputs. | • Preventive methods on cyber security (Cybulski and Scheepers 2021);<br>• Recursive model optimization to augment organizational knowledge (Harfouche et al. 2023). |
| 3 - AI-HI Hybrid | *Cooperation:* Humans and AIs work independently for certain tasks, sharing a portion of the decision-making process. Their outputs complement each other to collectively make decisions for the entire job. | • Surgical robots used in complicated surgeries (Makarius et al. 2020);<br>• Sequential interdependence systems (Lichtenthaler 2018; Paschen et al. 2020). |
| 4 - AI Decides, HI Controls | *Intervention:* AIs are programmed to produce final decisions, humans only intervene when anomalies are detected in outputs, by the means of correcting decision outputs or the needs to correct current models. | • Algorithmic matching and dynamic pricing (Möhlmann et al. 2021);<br>• Voice recognition assistance systems in banking services (Lui and Lamb 2018). |
| 5 - AI Decides, HI can Exit | *Rejection:* AI systems are responsible for producing decisions, humans have little control of modifying model, by opting out the entire use of the AI systems, ignore the AI recommendation support, or abandon algorithm models in certain application. | • Algorithm aversion (Kordzadeh and Ghasemaghaei 2022; Jussupow et al. 2020);<br>• Abandon system in non-routine situations (Stawarz et al. 2023);<br>• Mute unsatisfactory models (Asatiani et al. 2021). |
| 6 - AI Adapts, Eliminate HI | *Regulation:* AI systems are responsible for generating decisions, humans have limited control over modifying the results or the model, which leads to abandoning the AI systems or rejecting the AI model. | • Automation debt collecting systems (Braithwaite 2020);<br>• Smart contract for supply chain management (Murray et al. 2021). |

*Table 2. Human-AI Collaboration Configuration*

#### 4.2.1 AI suggests, HI decides (Configuration 1)

The typical application of AI in organizational decision-making involves using data to structure information and produce knowledge that informs rational decisions, as illustrated in (a) in Appendix C. This data-driven decision-making pattern is augmented by AI's processing capabilities, while human judgment remains the primary decision processor and is ultimately responsible for the decision outcome (Enarsson et al. 2022). The feedback loop between human judgment and AI is activated when new data is used for future information processing. In this loop, AI provides results that humans use as a tool, and they adjust their behavior to accommodate this assisted decision-making relationship (Benbya et al. 2021).

Medical diagnosis is an example of this configuration, providing physicians with a second opinion for their medical decisions (Jussupow et al. 2021). The ability of AI to efficiently analyze and categorize large amounts of heterogeneous data in time is a key advantage (Parent-Rocheleau and Parker 2022). However, this requires human decision-makers to be capable of sophisticatedly verifying AI-generated advice due to the absence of machine cognitive reasoning, particularly in complex contexts where the risk of misinformation is high (Jussupow et al. 2021).

#### 4.2.2 HI feedback, AI optimizes (Configuration 2)

Interactive machine-learning-powered AI systems require human actors to interact with them and leverage their capacities through intervention and feedback (Holzinger et al. 2019). In this configuration, the AI system automates decision-making tasks, but it is primarily supported by human actors who provide training data, correct decisions, or modify models (refer to (b) in Appendix C). Ongoing feedback from human actors provides more context-rich and timely data, refining the AI system and allowing for more accurate and appropriate decisions that are better aligned with the organization's needs, ultimately increasing its analytical capabilities for business strategy (Grønsund and Aanestad 2020).

For instance, a system designed for operational prediction in a freight business demonstrates its recursive and interactive nature in its adoption process (Grønsund and Aanestad 2020). However, AI can only optimize the detection model following security breaches in cyber security attacks (Cybulski and Scheepers 2021), hence, this configuration may require continuous human monitoring to keep the system evolving and functioning properly (Nahavandi 2017).

#### 4.2.3 AI-HI hybrid (Configuration 3)

The optimal combination of human and AI concepts involves an alternating role between human actors and one or more AI systems, allocating tasks that best suit them to achieve the decision objective (Sheridan 1995). This configuration (configuration 3, refer to (c) in Appendix C) requires a clear objective and explicit task breakdown, along with an advanced understanding of the advantages of HI and AI in the decision flow.

For example, such a system could allow clinicians to save effort on administrative and technological procedures, freeing them to attend to their patients' needs in person (Jotterand and Bosco 2020), and harness the big data processing advantage to develop operational strategies (Westphal et al. 2023). The best combination of human-AI collaboration seeks to leverage the strengths of both parties, with AI handling tasks that are prone to human errors (Nahavandi 2017; Fernández-Macías and Bisello 2022) or that require repetitive tasks (Sheridan 1995), while human actors provide ongoing feedback to signal control and verification to their AI partners. Nevertheless, achieving this "best" combination can be quantitatively challenging, particularly when there are conflicting objectives in a complex system (Sheridan 1995).

#### 4.2.4 AI decides, HI controls (Configuration 4)

The fourth configuration utilizes AI-enabled systems with greater autonomous power, in which the AI processes the task and produces the outcomes as the primary decision processor (refer to (d) in Appendix C). Human actors are the initial goal setters, who then step back from the primary decision-making loop and oversee the performance of the AI by monitoring the results (Parent-Rocheleau and Parker 2022). They only intervene when the outcomes deviate significantly from the initial goals, or if errors or biases are detected in the AI-generated outcomes (Nahavandi 2017). While the goals aim to ensure feedforward for higher accuracy, unlike human brains, AI systems still show limited capabilities to be adaptive and able to distinguish apparent decisions from circumstances that require judgment (Nahavandi 2017).

Therefore, human oversight is necessary to modify and control decision outputs, as in the case of a bank's lending and loan application systems, where approvals are automated as the preliminary processing loop. Bankers intervene only if discrepancies, such as discriminatory outcomes (Lee and Floridi 2021) or faulty decisions, are detected. In this configuration, higher transparency and explainability are demanded as human experts may not comprehend the cognitive reasoning of AI, which can impede their ability to effectively monitor decision performance (Enarsson et al. 2022; Parent-Rocheleau and Parker 2022).

### 4.2.5 AI decides, HI can exit (Configuration 5)

Ethical concerns have led to a growing body of literature that supports the idea of human actors having the right to opt-out of AI systems. For example, Zoom's use of sentiment analysis for customer relationship management has faced growing criticism due to issues such as data privacy and human rights (Giermindl et al. 2022). This perspective grants humans the right to opt-out, allowing them to decide whether to use AI systems or certain AI models (Asatiani et al. 2021), based on their own judgments (refer to (e) in Appendix C). It empowers them to make decisions independently instead of relying on AI recommendations (Parent-Rocheleau and Parker 2022). However, in some cases where AI systems have greater autonomy, human users have less control over decision outputs.

For example, people analytics software may replace direct communication for interactive employee assessment, leaving human actors less operable capacities (Giermindl et al. 2022). Due to decision responsibilities ultimately reside with humans, they may disregard AI suggestions (Rajpurkar et al. 2022) or avoid using AI systems altogether due to concerns about unfair outcomes (Asan et al. 2020).

### 4.2.6 AI adapts, eliminate HI (Configuration 6)

In the context of exponential growth in big data and the dynamic nature of target variables, new information can lead to the challenge of concept drift in machine learning predictions. Concept drift refers to the situation where the current model may become invalid for sustaining the expected accuracy for decision-making (de Lemos and Grześ 2019). One way to deal with this drift is through human control as stated in configuration 4. Conversely, an alternative solution is to enable AI systems to self-enhance. This self-adaptive form of interaction requires the involvement of human actors to identify the intended outcomes and purposes, allowing the system to sustain the output performance with new data models (Hauptman et al. 2023). Additionally, humans may need to define ethical and legal constraints that the system must adhere to (Enarsson et al. 2022). By setting these goals and constraints, humans provide a framework for the AI system to operate in, ensuring that the system keeps self-enhancing its actions while aligning with broader organizational objectives and ethical considerations (refer to (f) in Appendix C). In extreme cases, the self-adaptive model will completely restrict human control, such as blockchain-based smart contract, in which human can only set action goals for the decision algorithm (Murray et al. 2021).

## 4.3 HI-AI Collaboration Matrix

Based on an assessment of the extent of human agency and the level of AI capabilities, we transpose the six HI-AI configurations along axes of control and feedback, to support a better understanding of how collaborative intelligence between human and AI is communicated and structured (Webster and Watson 2002). This addresses research objective (3) on exploring how the six configurations are related. The vertical axis evaluates the extent of human control residing in each form of agency. According to the literature, the notion of "control" is contingent on the degree to which an AI system provides humans with the ability to influence decisions or algorithm outcomes (outcome control) as well as the processes to achieve outcomes (process control) (Kordzadeh and Ghasemaghaei 2022).

Outcome control includes human users' rights and ability to solve problems, improve situations or reject decisions (Fernández-Macías and Bisello 2022), whereas process control denotes human users' freedom on selecting their actions, or influence AI rules and logics (Lee and Floridi 2021). The level of control can be interpreted through the receptiveness of human users towards their AI teammates, where a higher control implies that humans view AI more as a tool (Hauptman et al. 2023) with higher control over the decision results (Westphal et al. 2023). To define the level of control, we consider the amount of human inputs involved in both outcome control and process control that the subject human making or acting upon a decision (Hauptman et al. 2023).

Our second axis introduces the notion of "feedback" to examine the characteristics of AI technologies, assessing system's learning capabilities. The feedback concept used in engineering studies refers to machine responses to control interventions (Cybulski and Scheepers 2021), which echoes the recent AI studies on “learning algorithms”, with which AI systems are capable to be adaptive (Akata et al. 2020) and interactive (Holzinger et al. 2019). These AI algorithms are capable to learn from big data and perform human-like cognitive tasks, such as application in people analytics (Giermindl et al. 2022), which also show strong abilities to learn from past decisions and newly added data without material needs for human intervention (Akata et al. 2020; Parent-Rocheleau and Parker 2022). Therefore, we scale feedback with AI learning capabilities against rule-based systems, which gives us the following configuration matrix illustrated in the following Figure 1.

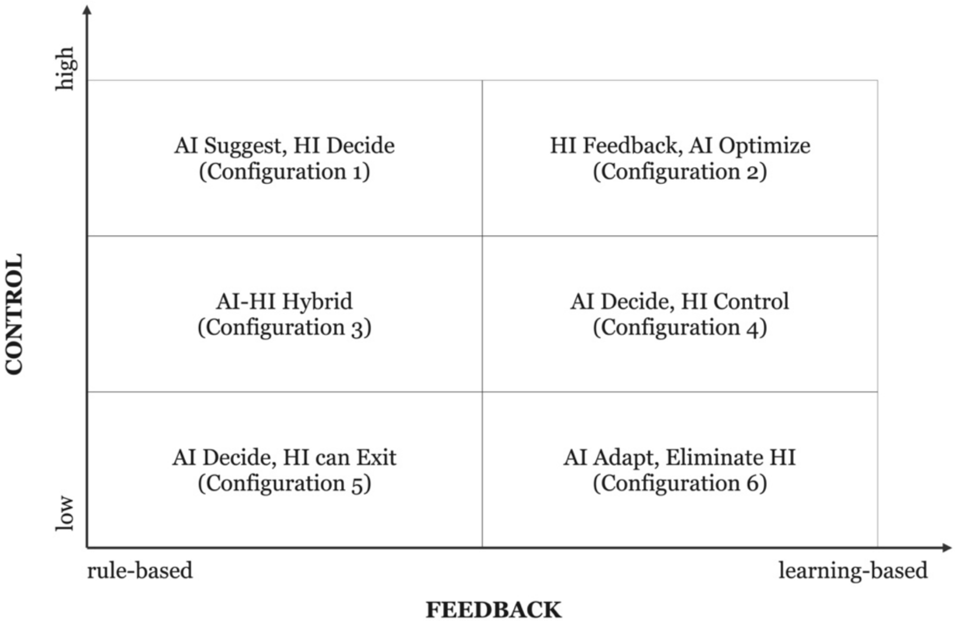


*Figure 1: HI-AI collaboration matrix*

# 5. Discussion

Motivated by organizing the current AI literature to obtain a deeper understanding of human roles in the AI-enabled decision-making phenomenon, we identified six types of human agency that characterize the ways in which human actors work with AI systems in organizational settings and corresponding HI-AI collaboration configurations. We then introduced a matrix to spell out the identified six configurations. Our HI-AI collaboration matrix framework clarifies conceptions of human-AI collaboration patterns, to achieve a more nuanced understanding of the balance of collaborative intelligence between the two.

Hence, our framework extends current research by enabling researchers to demonstrate the specific configuration in which their work is situated and what human agency and technical components are involved in that configuration. By incorporating both human and technical components, our framework offers a more comprehensive perspective on human-AI collaboration, which addresses the polarized focus on decision process automation (Arnott et al. 2017; Lichtenthaler 2018; Namvar et al. 2022). Thus, our framework can be particularly useful for AI researchers in comparing findings from their selected case studies that fall under different configurations, and therefore investigate the socio-technical components involved. This framework can also help to provide a common language for discussing human-AI collaboration and human agency, which can facilitate communication and collaboration between researchers working in different areas of AI.

## 5.1 Calibrate Human Agency in the Decision Process

The benefits of conceptual clarity extend to an enhanced understanding of human roles in the decision-making process. First, our HI-AI collaboration framework, with its six configurations, sheds light on the different levels of control and feedback possessed by humans in previous AI research. Based on the literature, we identified two generic forms of agency that humans can take: taking control and providing feedback (Figure 1), which are not mutually exclusive but differentiated into diverse collaborative configurations with changing evaluative scales. Humans create controls at the same time as they are constrained by AI models, leading to different types of human agency that reside in human actors (Kordzadeh and Ghasemaghaei 2022). For instance, human agency in terms of decision-making control are high in Configuration 1, while in Configuration 5 control is significantly reduced. As human actors bear ultimate accountability for the consequences of decisions, they may dissolve the partnership with AI systems should they perceive such collaboration exceed their control capacity (Giermindl et al. 2022; Rajpurkar et al. 2022). In this light, our six configurations and the matrix advance the understanding on how different configurations for human-AI collaboration affect the associated consequences of decision-making process, and facilitate the explanation on how human-AI collaboration configurations adapt in alignment with human-defined control goals (Benbya et al. 2021; Teodorescu et al. 2021).

Our six HI-AI configurations emphasize the importance of assigning decision-making tasks to the appropriate human decision-makers, avoiding any confusion about their roles and authorities. This clarity enables human adopters to better understand their expected agency, resulting in a more effective allocation of human resources within the given boundaries (Akata et al. 2020; Murray et al. 2021). By contrast, the level of feedback is determined by the technology, and configurations that require a high level of feedback (such as Configuration 2, 4, and 6) may blur the boundaries between human roles (Waardenburg and Huysman 2022). As a result, it is necessary to team-up human roles both in control and feedback loops to ensure accurate codification of domain knowledge in the model (Gronsund and Aanestad 2020) and to maintain the validity of the outputs (Rahwan 2018; Seidel et al. 2019; Braithwaite 2020).

## 5.2 Surface Risks and Limitations in AI-based Decision-Making

Second, our framework contributes to understanding risks associated with each configuration, therefore assisting organizations to be mindful of limitations. Configurations with high human control (i.e., Configuration 1 and 2) may encounter the risk of over-reliance on AI-generated recommendations (Giermindl et al. 2022), which deskills humans due to the investment in parallel learning on both human and machine is costly (Lebovitz et al. 2021). Furthermore, a deskilling in organizational human resources may hinder the feedback effectiveness for enhancing models, thus paradoxically show greater demands on human involvements (Kumar 2017; Benbya et al. 2021). For example, medical doctors dismissed their own diagnosis even though they are correct, due to the dismissed decision not being recommended by AI systems (Giermindl et al. 2022), which requires additional training (Jussupow et al. 2021).

Furthermore, configurations with high learning capacities (i.e., Configuration 2, 4 and 6) are vulnerable to automation bias, resulting in potential implementation failures to identify errors and biases in opaque self-adaptive AI technologies (Meske et al. 2022). This vulnerability can be mitigated by greater human control, otherwise resulting in including the avoidance of technology use and adverse consequences related to decision-making outcomes, particularly seen in Configuration 6 in which control is low. For example, reluctance to use AI systems for automated medical diagnoses (Coombs et al. 2020; Sturm et al. 2021).

## 5.3 Raise Awareness for Human-AI Balance in Decision-Making

Third, our framework serves as an index of empirical settings for organization users, offering guidance for comprehending the situated configuration in their AI adoptions and being vigilant about associated risks mentioned above in their current setups. Furthermore, it furnishes organizational users with insights on recalibrating human-AI configurations to align with their AI investment strategies and the imperatives to harness more advanced AI technologies to leverage their decision-making capability.

Hence, the technological change underscores the need to redesign decision-making processes and reconfigure the corresponding social and technical resources to achieve successful AI deployments (Coombs et al. 2020), which may trigger a shift between configurations. Due to the current lack of understanding on different configurations, the ability to research emerging configurations is hindered. However, an adapted decision procedure can afford higher effectiveness in accordance with human beliefs and values in their individual organizational context (Sturm et al. 2021) and provide dynamics to exploit appropriate skill complementarity strategy based on available resources (Ågerfalk 2020; Akata et al. 2020). For example, creating a feedback loop to involve algorithm auditors to perform validation (Rahwan 2018) to maintain integrity and trustworthiness (Braithwaite 2020). Our configurations model can serve as a guide for orchestrating an organization's business processes to appropriately balance the technical and social aspects of human-AI collaboration.

# 6. Limitations

Our study is not without limitations. Firstly, we position the investigation at the meso-level of organizational decision-making, which limits explanation at the micro-level, such as time and psychological pressure in highly turbulent situations (Aversa et al. 2018; Kordzadeh and Ghasemaghaei 2022) or type of decisions (Arnott et al. 2017; Giraud et al. 2022; Fernández-Macías and Bisello 2022). Nonetheless, the micro-level is also relevant for assessing and building configurations of human-AI collaborations. Future research could investigate individual stakeholders' behaviors that probe how individual traits affect their perceptions on teaming with AI systems, as well as how decision characteristics affect the collaborative setups between human and AI (Teodorescu et al. 2021).

Secondly, our framework is developed based on existing literature and may not fully capture all possible configurations or variations in practice. We therefore suggest future research examine our configurations in greater depth with empirical inquires (Murray et al. 2021; Sturm et al. 2021; Herrmann and Pfeiffer 2022), such as case studies and comparative studies. Lastly, we have not investigated the feedback loops in detail, which offers future opportunities to investigate feedback and its associated changes in the increasingly blurry human roles (Bauer et al. 2021; Waardenburg and Huysman 2022).

# 7. Conclusion

This review paper builds on the concept of human-AI collaboration to provide a framework for Human-AI collaborative intelligence. To address challenges brought by AI adoption, organizations are advised to keep human participation when automating decision-making procedures (Herrmann and Pfeiffer 2022), requiring new approaches to coordinating synthesized intelligence (Seeber et al. 2020). Our HI-AI configuration framework suggests different roles for human agency and visualizes collaborative configurations explained through the notions of control and feedback.

The six configurations are set to facilitate better understanding of human-AI collaboration to lift the full potential and benefits in practice (Johnson and Vera 2019; Rai et al. 2019), helping organizations to deploy resources (Weber et al. 2022) or plan their AI projects (Giraud et al. 2022). Hence, our review addresses the increasing interest of AI deployments in decision practices (Chui et al. 2022). In addition, our matrix framework contributes to a theoretical foundation for future research to better situate their studies regarding different HI-AI configurations, and thus as an index for their choices of case studies, with the potential to enhance communication and collaboration between researchers working in different areas of AI.

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Ulfert, A. S., Antoni, C. H., and Ellwart, T. 2022. "The Role of Agent Autonomy in Using Decision Support Systems at Work," *Computers in Human Behavior* (126), p. 106987.

van den Broek, E., Sergeeva, A., and Huysman, M. 2021. "When the Machine Meets the Expert: An Ethnography of Developing Ai for Hiring," *MIS Quarterly* (45:3), pp. 1557–1580.

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# 8. Appendix A– Search and acquisition strategy

| **Itera tion** | **Searching, sorting and selecting** | **Acquiring** | **Identifying and refining** |
|---|---|---|---|
| 1 | Selection keywords of "AI" OR "Artificial intelligence" OR "Machine learning" OR "ML" OR "Deep learning "OR "Business intelligence" AND "Decision support". Limit to *year after 2013* and *review* papers | 36 | Conceptualizing "AI used for organizational decision-making"; Identifying new search terms with the literature. |
| 2 | Selection keywords of "Human agency" OR "Human-AI collaboration" OR "Collaborative agency" OR "Human- | 24 | Peal growing new articles, leading to |

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|---|---|---|---|
| | centered machine learning" OR "AI teammate" OR "Conjoined agency" OR "Human in the loop". Exclude *subject areas* of mathematics, energy and so on, exclude *document type* of books, book review and conference paper. | | defining new terms for next iteration. |
| 3 | Selection keywords of "Human-centered machine learning" OR "AI teammate" OR "Conjoined agency" OR "Human in the loop". Sort articles by *ranking* and *publication date.* | 12 | Exit the first hermeneutic circle since little value and novelty were seen in additional searches. |
| **Total** | | **72** | |

# Appendix B – Full Articles List

| # | Articles | Agency | Configuration |
|---|---|---|---|
| 1 | Ågerfalk, P. J. 2020. "Artificial Intelligence as Digital Agency," *European Journal of Information Systems* (29:1), pp. 1–8. | Intervention, Regulation | 4, 6 |
| 2 | Akata, Z., Balliet, D., de Rijke, M., Dignum, F., Dignum, V., Eiben, G., Fokkens, A., Grossi, D., Hindriks, K., Hoos, H., Hung, H., Jonker, C., Monz, C., Neerincx, M., Oliehoek, F., Prakken, H., Schlobach, S., van der Gaag, L., van Harmelen, F., van Hoof, H., van Riemsdijk, B., van Wynsberghe, A., Verbrugge, R., Verheij, B., Vossen, P., and Welling, M. 2020. "A Research Agenda for Hybrid Intelligence: Augmenting Human Intellect With Collaborative, Adaptive, Responsible, and Explainable Artificial Intelligence," *Computer* (53:8), pp. 18–28. | Verification, Supervision, Cooperation | 1, 2, 3 |
| 3 | Amershi, S., Cakmak, M., Knox, W. B., and Kulesza, T. 2014. "Power to the People: The Role of Humans in Interactive Machine Learning," *AI Magazine* (35:4), pp. 105–120. | Supervision | 2 |
| 4 | Aoki, N. 2021. "The Importance of the Assurance That 'Humans Are Still in the Decision Loop' for Public Trust in Artificial Intelligence: Evidence from an Online Experiment," *Computers in Human Behavior* (114), p. 106572. | Verification | 1 |
| 5 | Arnott, D., Lizama, F., and Song, Y. 2017. "Patterns of Business Intelligence Systems Use in Organizations," *Decision Support Systems* (97), pp. 58–68. | Verification | 1 |
| 6 | Asatiani, A., Malo, P., Nagbøl, P. R., Penttinen, E., Rinta-Kahila, T., and Salovaara, A. 2021. "Sociotechnical Envelopment of Artificial Intelligence: An Approach to Organizational Deployment of Inscrutable Artificial Intelligence Systems," *Journal of the Association for Information Systems* (22:2), pp. 325–352. | Verification, Supervision, Rejection | 1, 2, 5 |
| 7 | Asan, O., Bayrak, A. E., and Choudhury, A. 2020. "Artificial Intelligence and Human Trust in Healthcare: Focus on Clinicians," *Journal of Medical Internet Research* (22:6), p. e15154. | Verification, Rejection | 1, 5 |
| 8 | Aversa, P., Cabantous, L., and Haefliger, S. 2018. "When Decision Support Systems Fail: Insights for Strategic Information Systems from Formula 1," *The Journal of Strategic Information Systems* (27:3), pp. 221–236. | Verification | 1 |
| 9 | Balasubramanian, N., Ye, Y., and Xu, M. 2022. "Substituting Human Decision-Making with Machine Learning: Implications for Organizational Learning," *Academy of Management Review* (47:3), pp. 448–465. | Regulation | 6 |
| 10 | Bauer, K., Hinz, O., van der Aalst, W., and Weinhardt, C. 2021. "Expl(AI)n It to Me – Explainable AI and Information Systems Research," *Business & Information Systems Engineering* (63:2), pp. 79–82. | Verification | 1 |
| 11 | Benbya, H., Pachidi, S., and Jarvenpaa, S. L. 2021. "Special Issue Editorial: Artificial Intelligence in Organizations: Implications for Information Systems Research," *Journal of the Association for Information Systems* (22:2), pp. 281–303. | Cooperation, Regulation | 3, 6 |
| 12 | Berger, B., Adam, M., Rühr, A., and Benlian, A. 2021. "Watch Me Improve—Algorithm Aversion and Demonstrating the Ability to Learn," *Business & Information Systems Engineering* (63:1), pp. 55–68. | Intervention, Rejection | 4, 5 |
| 13 | Bodén, A. C. S., Molin, J., Garvin, S., West, R. A., Lundström, C., and Treanor, D. 2021. "The Human-in-the-Loop: An Evaluation of Pathologists' Interaction with Artificial Intelligence in Clinical Practice," *Histopathology* (79:2), pp. 210–218. | Intervention | 4 |
| 14 | Braithwaite, V. 2020. "Beyond the Bubble That Is Robodebt: How Governments That Lose Integrity Threaten Democracy," *Australian Journal of Social Issues* (55:3), pp. 242–259. | Rejection | 5 |
| 15 | Burr, C., Cristianini, N., and Ladyman, J. 2018. "An Analysis of the Interaction Between Intelligent Software Agents and Human Users," *Minds and Machines* (28:4), pp. 735–774. | Regulation | 6 |

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| 16 | Cabitza, F., Campagner, A., and Simone, C. 2021. "The Need to Move Away from Agential-AI: Empirical Investigations, Useful Concepts and Open Issues," *International Journal of Human-Computer Studies* (155), p. 102696. | Verification | 1 |
| 17 | Coombs, C., Hislop, D., Taneva, S. K., and Barnard, S. 2020. "The Strategic Impacts of Intelligent Automation for Knowledge and Service Work: An Interdisciplinary Review," *The Journal of Strategic Information Systems* (29:4), p. 101600. | Verification, Regulation | 1, 6 |
| 18 | Cui, G., Wong, M. L., and Wan, X. 2012. "Cost-Sensitive Learning via Priority Sampling to Improve the Return on Marketing and CRM Investment," *Journal of Management Information Systems* (29:1), pp. 341–374. | Verification | 1 |
| 19 | Cybulski, J. L., and Scheepers, R. 2021. "Data Science in Organizations: Conceptualizing Its Breakthroughs and Blind Spots," *Journal of Information Technology* (36:2), pp. 154–175. | Supervision | 2 |
| 20 | Davenport, T., Guha, A., Grewal, D., and Bressgott, T. 2020. "How Artificial Intelligence Will Change the Future of Marketing," *Journal of the Academy of Marketing Science* (48:1), pp. 24–42. | Verification, Supervision, Cooperation, Regulation | 1, 2, 3, 6 |
| 21 | de Lemos, R., and Grześ, M. 2019. "Self-Adaptive Artificial Intelligence," in *2019 IEEE/ACM 14th International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS)*, May, pp. 155–156. | Regulation | 6 |
| 22 | Dilsizian, S. E., and Siegel, E. L. 2014. "Artificial Intelligence in Medicine and Cardiac Imaging: Harnessing Big Data and Advanced Computing to Provide Personalized Medical Diagnosis and Treatment," *Current Cardiology Reports* (16:1), p. 441. | Verification, Cooperation | 1, 3 |
| 23 | Duan, Y., Edwards, J. S., and Dwivedi, Y. K. 2019. "Artificial Intelligence for Decision Making in the Era of Big Data – Evolution, Challenges and Research Agenda," *International Journal of Information Management* (48), pp. 63–71. | Verification, Supervision, Cooperation | 1, 2, 3 |
| 24 | Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., and Janssen, M. 2021. "Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, Practice and Policy," *International Journal of Information Management* (57), p. 101994. | Verification, Supervision, Cooperation, Intervention | 1, 2, 3, 4 |
| 25 | Enarsson, T., Enqvist, L., and Naarttijärvi, M. 2022. "Approaching the Human in the Loop – Legal Perspectives on Hybrid Human/Algorithmic Decision-Making in Three Contexts," *Information & Communications Technology Law* (31:1), pp. 123–153. | Verification, Cooperation, Intervention | 1, 3, 4 |
| 26 | Fabri, L., Häckel, B., Oberländer, A. M., Rieg, M., and Stohr, A. 2023. "Disentangling Human-AI Hybrids: Conceptualizing the Interworking of Humans and AI-Enabled Systems," *Business & Information Systems Engineering*. | Cooperation, Intervention, Regulation | 3, 4, 6 |
| 27 | Fernández-Macías, E., and Bisello, M. 2022. "A Comprehensive Taxonomy of Tasks for Assessing the Impact of New Technologies on Work," *Social Indicators Research* (159:2), pp. 821–841. | Cooperation | 3 |
| 28 | Fügener, A., Grahl, J., Gupta, A., and Ketter, W. 2021. "Will Humans-in-the-Loop Become Borgs? Merits and Pitfalls of Working with Ai," *MIS Quarterly* (45:3), pp. 1527–1556. | Verification, Cooperation, Regulation | 1, 3, 6 |
| 29 | Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., and Redzepi, A. 2022. "The Dark Sides of People Analytics: Reviewing the Perils for Organisations and Employees," *European Journal of Information Systems* (31:3), pp. 410–435. | Verification, Intervention | 1, 4 |
| 30 | Giraud, L., Zaher, A., Hernandez, S., and Akram, A. A. 2022. "The Impacts of Artificial Intelligence on Managerial Skills," *Journal of Decision Systems*, pp. 1–34. | Cooperation, Intervention | 3, 4 |
| 31 | Gomes, P., Verçosa, L., Melo, F., Silva, V., Filho, C. B., and Bezerra, B. 2022. "Artificial Intelligence-Based Methods for Business Processes: A Systematic Literature Review," *Applied Sciences* (12:5), p. 2314. | Cooperation | 3 |
| 32 | Grønsund, T., and Aanestad, M. 2020. "Augmenting the Algorithm: Emerging Human-in-the-Loop Work Configurations," *The Journal of Strategic Information Systems* (29:2), p. 101614. | Intervention | 4 |
| 33 | Hauptman, A. I., Schelble, B. G., McNeese, N. J., and Madathil, K. C. 2023. "Adapt and Overcome: Perceptions of Adaptive Autonomous Agents for Human-AI Teaming," *Computers in Human Behavior* (138), p. 107451. | Verification, Regulation | 1, 6 |

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| 34 | Herm, L.-V., Heinrich, K., Wanner, J., and Janiesch, C. 2022. "Stop Ordering Machine Learning Algorithms by Their Explainability! A User-Centered Investigation of Performance and Explainability," *International Journal of Information Management*, p. 102538. | Verification | 1 |
| 35 | Herrmann, T., and Pfeiffer, S. 2022. "Keeping the Organization in the Loop: A Socio-Technical Extension of Human-Centered Artificial Intelligence," *AI & SOCIETY*. | Verification, Cooperation, Regulation | 1, 3, 6 |
| 36 | Harfouche, A., Quinio, B., Saba, M., and Saba, P. B. 2023. "The Recursive Theory of Knowledge Augmentation: Integrating Human Intuition and Knowledge in Artificial Intelligence to Augment Organizational Knowledge," *Information Systems Frontiers* (25:1), pp. 55–70. | Intervention | 4 |
| 37 | Holzinger, A. 2016. "Interactive Machine Learning for Health Informatics: When Do We Need the Human-in-the-Loop?," *Brain Informatics* (3:2), pp. 119–131. | Supervision | 2 |
| 38 | Johnson, M., and Vera, A. H. 2019. "No AI Is an Island: The Case for Teaming Intelligence," *AI Magazine* (40:1), pp. 16–29. | Supervision, Cooperation | 2, 3 |
| 39 | Jotterand, F., and Bosco, C. 2020. "Keeping the 'Human in the Loop' in the Age of Artificial Intelligence: Accompanying Commentary for 'Correcting the Brain?' By Rainey and Erden," *Science and Engineering Ethics* (26:5), pp. 2455–2460. | Cooperation | 3 |
| 40 | Jussupow, E., Spohrer, K., Heinzl, A., and Gawlitza, J. 2021. "Augmenting Medical Diagnosis Decisions? An Investigation into Physicians' Decision-Making Process with Artificial Intelligence," *Information Systems Research* (32:3), pp. 713–735. | Verification, Supervision | 1, 2 |
| 41 | Kane, G. C., Young, A. G., Majchrzak, A., and Ransbotham, S. 2021. "Avoiding an Oppressive Future of Machine Learning: A Design Theory for Emancipatory Assistants," *MIS Quarterly* (45:1), pp. 371–396. | Regulation | 6 |
| 42 | Kordzadeh, N., and Ghasemaghaei, M. 2022. "Algorithmic Bias: Review, Synthesis, and Future Research Directions," *European Journal of Information Systems* (31:3), pp. 388–409. | Rejection | 5 |
| 43 | Lebovitz, S., Levina, N., and Lifshitz-Assaf, H. 2021. "Is Ai Ground Truth Really True? The Dangers of Training and Evaluating Ai Tools Based on Experts' Know-What," *MIS Quarterly* (45:3), pp. 1501–1525. | Verification | 1 |
| 44 | Lee, M. S. A., and Floridi, L. 2021. "Algorithmic Fairness in Mortgage Lending: From Absolute Conditions to Relational Trade-Offs," *Minds and Machines* (31:1), pp. 165–191. | Supervision, Regulation | 2, 6 |
| 45 | Lichtenthaler, U. 2018. "Substitute or Synthesis: The Interplay between Human and Artificial Intelligence," *Research-Technology Management* (61:5), pp. 12–14. | Cooperation, Regulation | 3, 6 |
| 46 | Lui, A., and Lamb, G. W. 2018. "Artificial Intelligence and Augmented Intelligence Collaboration: Regaining Trust and Confidence in the Financial Sector," *Information & Communications Technology Law* (27:3), pp. 267–283. | Intervention | 4 |
| 47 | Mabrok, M. A., Mohamed, H. K., Abdel-Aty, A. H., and Alzahrani, A. S. 2020. "Human Models in Human-in-the-Loop Control Systems," *Journal of Intelligent & Fuzzy Systems* (38:3), pp. 2611–2622. | Regulation | 6 |
| 48 | Makarius, E. E., Mukherjee, D., Fox, J. D., and Fox, A. K. 2020. "Rising with the Machines: A Sociotechnical Framework for Bringing Artificial Intelligence into the Organization," *Journal of Business Research* (120), pp. 262–273. | Cooperation, Regulation | 3, 6 |
| 49 | Meske, C., Bunde, E., Schneider, J., and Gersch, M. 2022. "Explainable Artificial Intelligence: Objectives, Stakeholders, and Future Research Opportunities," *Information Systems Management* (39:1), pp. 53–63. | Cooperation, Regulation | 3, 6 |
| 50 | Murray, A., Rhymer, J., and Sirmon, D. G. 2021. "Humans and Technology: Forms of Conjoined Agency in Organizations," *Academy of Management Review* (46:3), pp. 552–571. | Verification, Rejection, Regulation | 1, 5, 6 |
| 51 | Namvar, M., Intezari, A., Akhlaghpour, S., and Brienza, J. P. 2022. "Beyond Effective Use: Integrating Wise Reasoning in Machine Learning Development," *International Journal of Information Management*, p. 102566. | Regulation, Intervention | 6, 4 |
| 52 | Paschen, J., Wilson, M., and Ferreira, J. J. 2020. "Collaborative Intelligence: How Human and Artificial Intelligence Create Value along the B2B Sales Funnel," *Business Horizons* (63:3), pp. 403–414. | Cooperation | 3 |

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| 53 | Pandey, R., Purohit, H., Castillo, C., and Shalin, V. L. 2022. "Modeling and Mitigating Human Annotation Errors to Design Efficient Stream Processing Systems with Human-in-the-Loop Machine Learning," *International Journal of Human-Computer Studies* (160), p. 102772. | Regulation | 6 |
| 54 | Parent-Rocheleau, X., and Parker, S. K. 2022. "Algorithms as Work Designers: How Algorithmic Management Influences the Design of Jobs," *Human Resource Management Review* (32:3), p. 100838. | Cooperation, Regulation | 3, 6 |
| 55 | Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.-F., Breazeal, C., Crandall, J. W., Christakis, N. A., Couzin, I. D., Jackson, M. O., Jennings, N. R., Kamar, E., Kloumann, I. M., Larochelle, H., Lazer, D., McElreath, R., Mislove, A., Parkes, D. C., Pentland, A. 'Sandy,' Roberts, M. E., Shariff, A., Tenenbaum, J. B., and Wellman, M. 2019. "Machine Behaviour," *Nature* (568:7753), pp. 477–486. | Intervention, Regulation | 4, 6 |
| 56 | Rajpurkar, P., Chen, E., Banerjee, O., and Topol, E. J. 2022. "AI in Health and Medicine," *Nature Medicine* (28:1), pp. 31–38. | Verification, Regulation | 1, 6 |
| 57 | Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G.-J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., and Söllner, M. 2020. "Machines as Teammates: A Research Agenda on AI in Team Collaboration," *Information & Management* (57:2), p. 103174. | Verification, Cooperation, Rejection | 1, 3, 5 |
| 58 | Seidel, S., Berente, N., Lindberg, A., Lyytinen, K., and Nickerson, J. V. 2018. "Autonomous Tools and Design: A Triple-Loop Approach to Human-Machine Learning," *Communications of the ACM* (62:1), pp. 50–57. | Cooperation, Regulation | 3, 6 |
| 59 | Shrestha, Y. R., Ben-Menahem, S. M., and von Krogh, G. 2019. "Organizational Decision-Making Structures in the Age of Artificial Intelligence," *California Management Review* (61:4), pp. 66–83. | Verification, Cooperation | 1, 3 |
| 60 | Simsek, S., Albizri, A., Johnson, M., Custis, T., and Weikert, S. 2020. "Predictive Data Analytics for Contract Renewals: A Decision Support Tool for Managerial Decision-Making," Journal of Enterprise Information Management (34:2), pp. 718–732. | Cooperation | 3 |
| 61 | Stawarz, K., Katz, D., Ayobi, A., Marshall, P., Yamagata, T., Santos-Rodriguez, R., Flach, P., and O'Kane, A. A. 2023. "Co-Designing Opportunities for Human-Centred Machine Learning in Supporting Type 1 Diabetes Decision-Making," *International Journal of Human-Computer Studies* (173), p. 103003. | Verification, Rejection | 1, 5 |
| 62 | Sturm, T., Gerlach, J. P., Pumplun, L., Mesbah, N., Peters, F., Tauchert, C., Nan, N., and Buxmann, P. 2021. "Coordinating Human and Machine Learning for Effective Organizational Learning," *MIS Quarterly* (45:3), MIS Quarterly, pp. 1581–1602. | Regulation | 6 |
| 63 | Taha, A. A., and Malebary, S. J. 2020. "An Intelligent Approach to Credit Card Fraud Detection Using an Optimized Light Gradient Boosting Machine," *IEEE Access* (8), pp. 25579–25587. | Regulation | 6 |
| 64 | Teodorescu, M. H. M., Morse, L., Awwad, Y., and Kane, G. C. 2021. "Failures of Fairness in Automation Require a Deeper Understanding of Human-Ml Augmentation," *MIS Quarterly* (45:3), pp. 1483–1499. | Supervision, Intervention | 2, 4 |
| 65 | Tolan, S., Pesole, A., Martínez-Plumed, F., Fernández-Macías, E., Hernández-Orallo, J., and Gómez, E. 2021. "Measuring the Occupational Impact of AI: Tasks, Cognitive Abilities and AI Benchmarks," *Journal of Artificial Intelligence Research* (71), pp. 191–236. | Cooperation | 3 |
| 66 | Tolmeijer, S., Christen, M., Kandul, S., Kneer, M., and Bernstein, A. 2022. "Capable but Amoral? Comparing AI and Human Expert Collaboration in Ethical Decision Making," in *CHI Conference on Human Factors in Computing Systems*, New Orleans LA USA: ACM, April 27, pp. 1–17. | Verification, Intervention | 1, 4 |
| 67 | Ulfert, A.-S., Antoni, C. H., and Ellwart, T. 2022. "The Role of Agent Autonomy in Using Decision Support Systems at Work," *Computers in Human Behavior* (126), p. 106987. | Verification, Intervention | 1, 4 |
| 68 | van den Broek, E., Sergeeva, A., and Huysman, M. 2021. "When the Machine Meets the Expert: An Ethnography of Developing Ai for Hiring," *MIS Quarterly* (45:3), pp. 1557–1580. | Regulation | 6 |
| 69 | Weber, M., Engert, M., Schaffer, N., Weking, J., and Krcmar, H. 2022. "Organizational Capabilities for AI Implementation—Coping with Inscrutability and Data Dependency in AI," *Information Systems Frontiers*. | Regulation | 6 |
| 70 | Westphal, M., Vössing, M., Satzger, G., Yom-Tov, G. B., and Rafaeli, A. 2023. "Decision Control and Explanations in Human-AI Collaboration: Improving User Perceptions and Compliance," *Computers in Human Behavior* (144), p. 107714. | Verification, Cooperation | 1, 3 |

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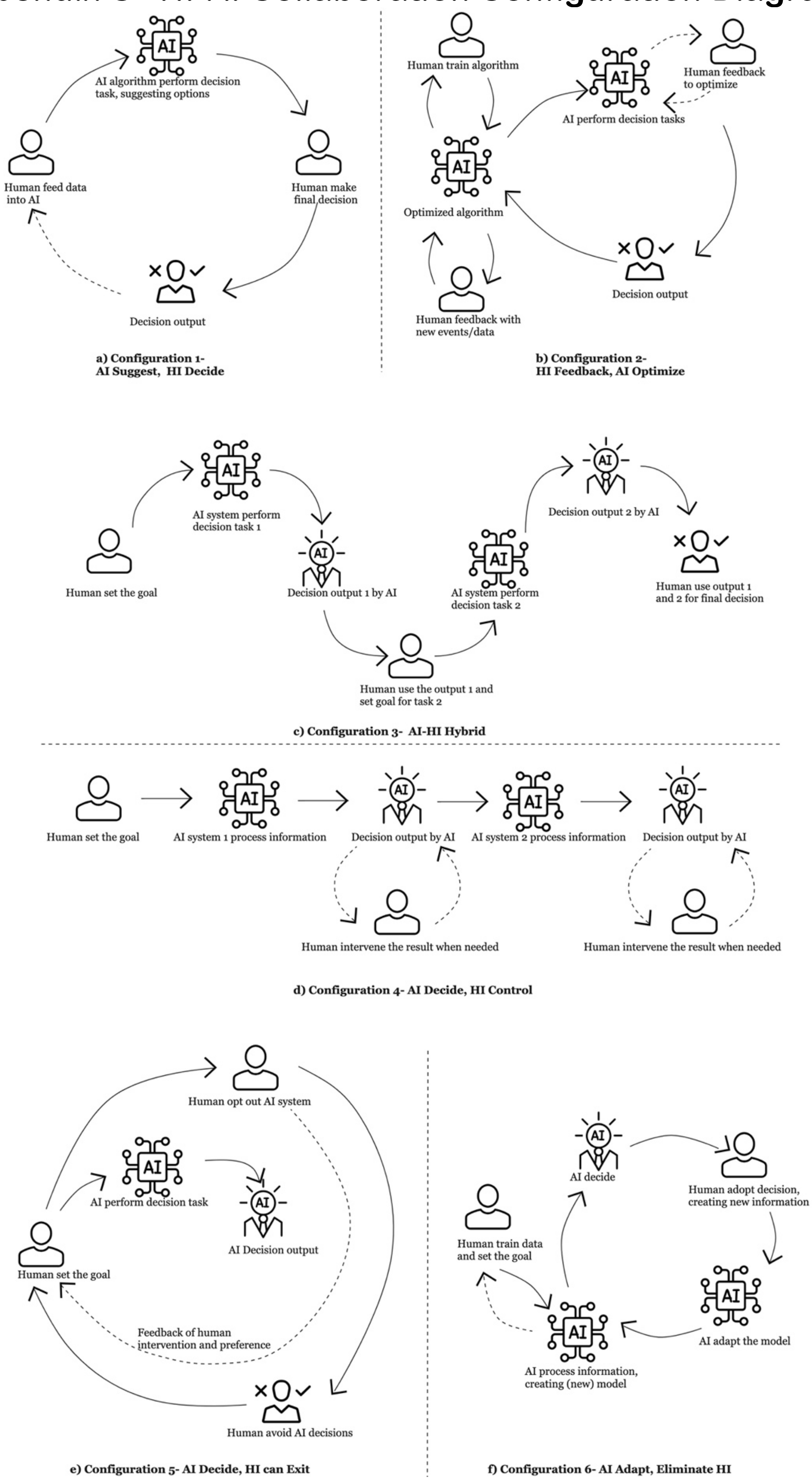
| 71 | Yang, Y., Truong, N. D., Maher, C., Nikpour, A., and Kavehei, O. 2022. “Continental Generalization of a Human-in-the-Loop AI System for Clinical Seizure Recognition,” *Expert Systems with Applications* (207), p. 118083. | Verification, Intervention | 1, 4 |
| 72 | Zanzotto, F. M. 2019. “Viewpoint: Human-in-the-Loop Artificial Intelligence,” *Journal of Artificial Intelligence Research* (64), pp. 243–252. | Intervention, Regulation | 4, 6 |

# Appendix C– HI-AI Collaboration Configuration Diagram



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