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Towards Hybrid Intelligence in Learning Organizations

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Abstract. The roles of humans and AI as the labor force of organizations need continuous re-evaluation with the advancement of AI. While automation has replaced some tasks, knowledge-intensive work environments rely on human intelligence, as those work practices transcend canonical procedures. We propose a hybrid intelligence methodology for organizations to address knowledge erosion. We contextualize this methodology in an example case study from the Legal Desk in the Netherlands, following the six principles of designing intelligent organizations [1], i.e., addition, relevance, substitution, diversity, collaboration, and explanation. We found that adhering to these six basic principles appeared to be a balancing act on two axes: contribution of AI versus human intelligence towards the tasks, and the way of working of human and artificial agents over time. We propose two additional principles. The first is human oversight, which highlights the importance of human control in organizational decision-making. The second principle is collaborative reflection which emphasizes the need to actively manage organizational intelligence. We also discuss the challenges to enable our methodology in the organizational context. This paper aims to inspire researchers and practitioners to pursue new initiatives towards achieving hybrid intelligence for learning organizations.

Keywords. hybrid intelligence, learning organization, human oversight, collaborative reflection, knowledge erosion

1. Introduction

Organizations today are facing an issue with knowledge erosion [2,3]. This phenomenon refers to the loss of critical knowledge and expertise due to employee turnover and generational shifts. When knowledge workers leave, organizations suffer from increased costs and decreased efficiency. This issue underscores the importance of creating a learning organization, an entity skilled in creating, acquiring, and transferring knowledge, and adapting workflows, systems, and decision-making to new insights [4].

Organizations are rapidly exploring and adopting artificial intelligence (AI)-based tools. Some have turned to AI to establish more advanced knowledge management systems. A notable example is the growing effort to create domain-specific, local language models tailored for organizational use [5]. Although this approach promises efficiency, it

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Table 1. Related research in AI-facilitated learning. The table is organized by categorizing works into theory and application approaches, across the individual, group, and organization scale.

	AI-facilitated learning	
	Theory and models	**Application**
Organization	organizational learning [1,9,10,11]	**Under-explored**
Group	group cognition [12,13,14]	online discussion [15] collaborative learning [16,17]
Individual	personalization [18,19,20]	self-directed learning [21,22] LLM interaction [23,24,25]

risks marginalizing human knowledge workers. Addressing knowledge erosion requires a balanced integration of technology and human expertise to ensure the relevance of human workers in the evolving workplace.

From our collaboration with the Legal Desk of the Netherlands, we learned that the organization is experiencing knowledge erosion and is, in parallel, trying to integrate more AI-based tools. To this end, we reflect on the organization's current practice and motivate the need for a hybrid learning organization. A hybrid learning organization is an ecosystem where humans and AI systems co-exist, interact, and co-evolve, creating an environment of continuous learning and mutual growth. Humans refine AI by providing input and feedback. AI systems enhance human understanding through data-driven insights. Through this mutual learning, a feedback loop is established, which ensures that humans and AI systems evolve in alignment with organizational goals and values. Organizations are often interpreted as a collection of working groups and teams [6]. As AI systems become more integrated with human teams and activities over time, scholars from diverse fields and expertise see this as an emerging field: human-AI co-evolution [7], a continuous and longitudinal trans-disciplinary human-AI interaction.

This paper describes a methodology where ***h***ybrid ***i***ntelligent technologies are part of the ***l***earning ***o***rganization system (HILO). We contextualize it with the current working situation of legal advisors at the Legal Desk, providing a real-world example of hybrid learning organization design. We discuss the methodology through intelligent organizations design principles [1] and the challenges in human-AI co-learning [8].

2. Knowledge Gap

Organizational learning describes institutional processes to ensure knowledge management, storage, and dissemination. Digital and AI-based tools have transformed how organizations handle data and knowledge, and how they learn as an entity. Table 1 lists some related research for AI-facilitated learning for individuals, groups, and organizations [2].

AI-facilitated organizational learning remains underexplored from an application perspective, likely due to the complexity introduced by the scale of organizations and the long-term nature of organizational learning processes. Several seminal papers have pointed out how organizational work practices and learning are intrinsically opposing

[2] We note that these dimensions of individual, group, and organizational learning, and theory vs. application-oriented work, are in practice a continuum. However, this division provides a way to situate our contribution.

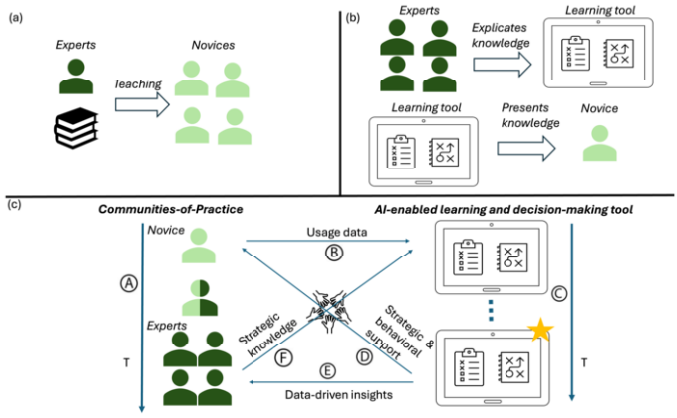

Figure 1. (a) a teacher-student pedagogy method; (b) a learning platform without AI capabilities; (c) proposed hybrid intelligence methodology for human-AI learning in organizations.

forces [26,27]. Rigid organizational cultures and defensive routines impede innovation-based learning. However, Nonaka and Takeuchi, and Lave and Wenger have theorized how Communities-of-Practices, groups that form around shared interests or expertise, could facilitate in breaking the barrier of learning by framing it as a social process [28,29]. While these organizational learning theories have laid the foundation as to *what* to implement [30], applications of these theories, as in *how* to implement remain challenging, and are further complicated by incorporating AI systems. In this paper, we take a step towards closing the gap between theories in AI-facilitated organizational learning and their implementation in an application scenario (i.e., the Legal Desk).

3. A Motivating Example from the Legal Desk

From Novice to Expert At the Legal Desk, legal advisors interface with clients who come to the counter desk for legal consultation. Common legal topics include labor, family, and tenancy law, among others. Some cases may involve multiple legal topics, making them more complex, and often require in-person consultation hours. New advisors are introduced to the general workflow, content materials, and technology infrastructure through on-boarding training (Figure 1(a) and (b)). Most of the working knowledge is learned on the job, taking new hires at least 1.5 years to become experienced advisors.

Legal advisors do not know beforehand the cases and situations that clients will bring to them. Hence, the work is diagnostic in nature and often deviates from the canonical procedure. These tacit knowledge and non-canonical practices are communicated in hallways or in Microsoft Teams chat and remain structurally undocumented. This informal exchange of knowledge in groups forms a Community-of-Practice, which helps to bridge the gap between their organization's static knowledge and the changing practices.

Designing a Hybrid Learning Organization The proposed hybrid learning organization methodology is shown in Figure 1(c), contrasting the current way of learning depicted in Figure 1(a) and (b). The methodology extends individual intelligence to Communities-of-Practice, facilitating the transition from novice to expert. From the AI-

centric perspective, it extends a single AI system to an agentic workflow where the AI systems collaborate with humans and iteratively improve themselves with historical data and user inputs, thereby achieving *augmented collective intelligence* [31].

4. Design Principles

Figure 1(c) shows example interactions within a hybrid learning organization. Novice advisors become experienced advisors over time (path A). In the meantime, novice users engage with an AI decision-making support tool (e.g. during consultations) to generate usage data (path B). The collected usage data serves as training input, enabling the AI systems to adapt algorithmically over time. AI systems continuously adapt to and learn from human feedback (path C). These AI systems could assist novices with their perceptive and problem-solving capabilities (e.g. suggesting sound legal advice) (path D). Furthermore, insights derived from active AI system usage highlight trends and anomalies in both task-related and human behavioral patterns, providing expert users with actionable information (path E). Through Communities-of-Practice, human experts provide feedback and fine-tune the AI systems, enabling continuous improvement (path F).

Reference Conceptual Frameworks We ground the proposed methodology in the principles for designing an intelligent organization, as outlined by Kolbjornsrud. These principles address six key aspects: (1) addition, (2) relevance, (3) substitution, (4) diversity, (5) collaboration, and (6) explanation. The *addition* principle assumes that incorporating human or artificial intelligence enhances organizational intelligence. The *substitution* principle posits that replacing human intelligence with artificial intelligence does not inherently lead to a more intelligent organization. We believe that the principles of *addition* and *substitution* are foundational assumptions underlying any hybrid intelligent technology, including our proposed methodology. Note that metrics are required to evaluate the organizational intelligence. We discuss our methodology in Section 4.1 with respect to the other four principles (relevance, diversity, collaboration, explanation).

We base our methodology and its entablement with the six challenges of human-AI co-learning proposed by van den Bosch et al. [8]. These challenges focus on developing respective models (applicable for humans and AI systems) to address the following goals: (1) building a shared *taxonomy*, (2) working agreements between the human-AI *team*, (3) common understanding of the *task* to be completed, (4) a *self* model (i.e., self-awareness of own capabilities, values, etc.), (5) a *Theory-of-Mind* (ToM) model (i.e., awareness of other agents' capabilities, values, etc.), and finally (6) a *communication* model for explaining to other agents. We discuss these challenges for hybrid learning organizations.

4.1. Design principles for learning organizations

Relevance This principle states that "the type of intelligence must match the nature of the task". While this principle seems obvious, in practice it is difficult to ensure. In our case, we design the human-human Communities-of-Practice group learning pathway to ensure human connections at the workplace. The emotional bond and interpersonal skills that experienced advisors have are essential for novice advisors' personal growth and development [32]. In groups, human advisors can understand, empathize, and motivate students in a way that AI cannot. Human's unique strength in connecting with others is

leveraged, especially as AI systems don't currently possess this level of interpersonal and social capability. In contrast to humans, AI systems could be an always available learning partner, to up-skill novice advisors by providing real-time and on-demand decision-making support. To evaluate relevance, a proxy could be to apply some measure for task performance, e.g., expert evaluation of outcome quality, or organizational efficiency.
Challenge: To establish relevance, i.e., deciding whether AI, or humans, or human-AI teams, should do a certain type of task, would require humans and AI systems to establish a common taxonomy (shared vocabulary) and task model. Humans and AI systems should also establish a self-model, i.e., knowledge about themselves, and other agents (Theory-of-mind model). Establishing these models requires a shared communication model. For instance, at an early stage of deployment, the AI agent should report its uncertainty on the strategic support for legal advice, and delegate to humans when needed.

Diversity The diversity principle states that "having diverse skills and levels of skill, in either human or artificial form, increases organizational intelligence". In our methodology, a mix of novice, intermediate, and expert skills ensures a dynamic flow of knowledge transfer. Novices also contribute meaningfully to the development of AI systems and provide fresh perspectives to human experts. Having different levels of AI functionalities is beneficial from an organizational efficiency viewpoint: simpler agents might efficiently handle routine tasks (e.g., automated dashboard reporting), while more advanced systems could be useful in more complex interactions (e.g. recommend options for legal advice). Evaluating the successful application of this principle entails measuring the organizational intelligence before and after implementing the principles.
Challenge: Implementing diverse human-AI interactions presents challenges in constructing robust task models and self- and Theory-of-Mind models. Both humans and AI systems need an accurate understanding of each other's capabilities and limitations. This requires a shared taxonomy and communication model. E.g. AI systems could handle repetitive work, freeing humans for higher-valued, creative, or strategic tasks.

Collaboration The collaboration principle states that "organizational intelligence requires collaborative skills from both human and AI systems". In Figure 1(c), we show the collaborative interactions and feedback loops between humans and human-AI systems. Previous research has explored the effects of human-AI feedback loops, such as how user engagement with recommendation systems declines over time, leading to a degeneration of the feedback mechanism [33]. In our methodology, similar challenges may arise when AI systems provide legal advice to novice users or present insights to expert users. To assess the effect of such feedback loops, outcomes need to be measured after iteration, that is every time that the AI-systems are retrained and human behavior changes. The granularity at which the impacts are measured, as well as the methods used to assess impacts, are design choices that need to be motivated for each organizational context. To evaluate the influence of the collaboration principle, one could compare measures on the displayed collaborativeness of the organization before and after implementing the methodology. The literature on learning organizations and on teamwork (and human-agent teamwork) provides examples of such behaviors [27,34,35,36].
Challenge: Establishing collaborations within the organization is challenging and is further complicated with the integration of AI. In addition to the challenges in developing task, self, and Theory-of-Mind models, a team model needs to be established. In our methodology, we emphasize the dynamics of interactions across novice-expert, expert-

expert, novice-AI, expert-AI, and AI-AI (within a multi-agent workflow). Novice-expert and expert-expert interactions address organizational challenges to create a culture of learning, cultivating Communities-of-Practice. Novice-AI and expert-AI collaborations explore human-AI synergies, with research challenges rooted in human-AI interaction, explainable AI, in the broader context of computer-supported cooperative work. AI-AI collaborations create multi-agent workflows to enable groups of intelligent agents to coordinate, share knowledge, and solve problems collectively. These interactions demand bi-directional learning and adaptation between humans and AI or between AI agents [7].

Explanation The explanation principle states that the "organizations seek explanation and act responsibly". This principle aligns well with the hybrid intelligence research agenda that AI systems need to be explainable and realize responsibility [37]. In our methodology, the AI systems should be interpretable to humans and explain how recommended legal advice is reached. Advisors also need to be able to explain themselves in decision-making during legal consultation and knowledge exchange in Communities-of-Practice. To evaluate the effectiveness of adhering to this principle, one can apply expert evaluations of randomly selected actions of the organization or assess the contestations made by those affected by actions of the organization.
Challenge: Establishing explainability is one of the challenges in achieving human-AI co-learning [8] and supports the establishment of the models. Vice-versa, the shared taxonomy and the models are needed to realize explainability. In our case study with the Legal Desk, we posit that the need for explainability could be situational (e.g., necessary in high-stakes scenarios according to organizations' evaluation, but optional for other scenarios). Explanations should be formulated at different levels of granularity and from different perspectives, according to different human users [38].

Gap in Existing Principles We propose adding two additional principles: *dynamic balance between human and AI intelligence with human oversight* and *collaborative reflection to regularly and actively manage organizational intelligence*. Dynamic balancing between human and AI intelligence is required given the tasks and in accordance with the principle of relevance. However, that does not cover the principle that humans should have the ability and authority to control the hybrid intelligent learning systems to realize their responsibility towards the organization. This principle is founded in the work on human oversight and meaningful human control [39,40,41] and is related to the principle of explanation. The need for collaborative reflection as part of organizational development is motivated by previous research showing the impact of reflection on increased learning and professional development [42]. In collaborative reflection, participants (human or AI) jointly share their reflections, where participants exercise systems thinking, in terms of their contribution towards the organization's long-term success.

4.2. Dynamic Balance of Human and AI Intelligence with Human Oversight

In organizational settings, particularly in high-stakes decision-making scenarios, achieving a dynamic balance between humans and AI systems needs to be considered. This balance involves carefully considering authority, ability, responsibility, and control in shared and cooperative contexts [43]. Depending on the task and situation, humans should retain control and authority over AI systems to ensure meaningful oversight [39].

When providing legal advice, human advisors grasp nuances, exceptions, or contextual insights, that AI may miss, especially early on. In an anecdotal example, a client

wanted to stay in the Netherlands after ending a relationship with a Dutch partner. Unsure if the ex-partner had reported the breakup, as required by immigration rules, she considered doing it herself. However, the advisor recommended that the client focus on finding employment to extend her stay, as her residence permit remained valid. This example highlights the importance of human judgment and control in interpreting regulations and advising clients effectively. To evaluate the effectiveness of adhering to the principle of human oversight, one can measure the frequency of human interventions and the explanations surrounding human intervention by properly logging events.
Challenge: The example above illustrates the complexity of decision-making in providing legal advice. In such scenarios, human control is important, as the approach and the resulting advice should reflect personal, professional, and organizational values and a situational understanding that AI systems may not yet fully capture. This limitation arises from challenges in developing situational awareness. A shared taxonomy, team, task, and communication model is needed to adequately intervene. It is also necessary to establish clear agreements under human oversight, on *how* and *when* AI agents can dynamically intervene in work activities. These measures ensure that AI systems complement, rather than compromise, human decision-making and organizational integrity.

4.3. Collaborative Reflection

Collaborative reflection involves multiple participants coming together to share their experiences, perspectives, and insights, creating a collective understanding that goes beyond individual capabilities [44]. By establishing learning and reflection loops, we leverage multi-lifespan design thinking [45]. This is an approach to design that focuses on addressing complex and long-term organizational challenges by creating knowledge that spans many years, which, in this case, pertains to advisors' years of working at the organization [46,47]. Collaborative reflections enable all organizational participants to actively seek, preserve, and use organizational intelligence. To evaluate the effectiveness of implementing collaborative reflection, one can measure the knowledge gain, e.g., by measuring the magnitude and frequency of changes made to the system by the collaborative reflection activities (path F in Figure 1(c)).
Challenge: Challenges in enabling collaborative reflection include establishing a shared taxonomy, task-, self-, Theory-of-Mind, and communication model. In addition to the mentioned challenges, collaborative reflection requires trust and empowerment of organizational members. Complexities arising from continuous human-AI feedback mechanism in achieving human-AI co-evolution include the possibility of models excessively adapting to certain users' feedback [48]. This inadvertently creates an echo chamber of humans and AI systems, which reduces the learning capacity of the organization. Implementing collaborative reflections of multiple humans and the AI systems instead increases the learning capacity of the hybrid organization.

4.4. Summary of Contribution

We summarize our contribution for a Hybrid Intelligence methodology for Learning Organizations (HILO) in Table 2. We discussed the methodology concerning the six principles of intelligent organization design proposed by Kolbjørnsrud[1] with an extension of additional principles of Human Oversight and Collaborative Reflection (column 1 in

Table 2). The human-AI co-learning challenges proposed by Van de Bosch et al. [8] are addressed with the related models (row 1 in Table 2). The last column summarizes the required metrics to evaluate the successful application of the HILO methodology. We also explain how implementing the HILO principles would materialize Figure 1(c) and close the continuous feedback loop that captures the hybrid learning capacity.

Table 2. Matching HILO Principles to Human-AI co-learning models [8] and required evaluation metrics, where R means "principle requires model", S means "principle supports model formation", and E means "principle is needed to establish the model". The principles Addition through Explanation stem from [1], Human Oversight and Collaborative Reflection are specific to HILO.

	Human-AI co-learning models						
HILO Principles	**Taxonomy**	**Team**	**Task**	**Self**	**Theory-of-Mind**	**Communication**	**Required metrics**
Addition							Organizational intelligence
Substitution							Organizational intelligence
Relevance	R		R	R	R	R	Task performance
Diversity	R		R	R	R	R	Organizational intelligence
Collaboration	R	R	R	R	R	R	Collaborative behaviour
Explanation	R	RS	RS	RS	RS	R	Contestations
Human Oversight	R	R	R			R	Interventions
Collaborative Reflection	R	E	E	S	E	R	Knowledge gain

5. Relevance and Outlook

The full potential of the proposed methodology requires enabling all pathways in Figure 1(c). Yet an important observation is that implementing even a subset of human-human, human-AI, and AI-AI learning pathways could already enhance organizational intelligence. This modular design reduces the complexities of implementing the entire system at once, making it more practical for organizational adoption.

Establishing human-AI learning communities represents a paradigm shift in both organizational learning and artificial intelligence. These communities should cultivate an environment where humans and AI co-create collective intelligence under human oversight to ensure a constructive balance. This transition elevates AI from a passive tool to an active participant in the learning ecosystem. However, this shift also places new demands on skills and competencies on AI awareness and literacy.

While our proposed methodology outlines how organizations could implement a hybrid learning environment, the challenges discussed remain active areas of research. We see the potential of hybrid learning organizations in practical scenarios where knowledge workers develop their expertise, while changes in contexts, as seen, for example, in the legislation and regulations regarding immigration, and/or a high employee turnover rate, pose extra reasons for implementing a hybrid learning environment.

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