Human-AI Shared Regulation for Hybrid Intelligence in Learning and Teaching: Conceptual Domain, Ontological Foundations, Propositions, and Implications for Research

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Abstract

In today's rapidly evolving and technology-integrated society, the role of Artificial Intelligence (AI) in co-learning, co-working, and co-evolution is garnering increasing attention from both practitioners and researchers. Despite this growing interest, systematic scholarly inquiry into the concept of Hybrid Intelligence (HI), which combines human intelligence and AI, and its distinctiveness from other related concepts, has been limited. This article explores the theoretical foundations and philosophical perspectives of HI in the context of Information Systems (IS) research. Specifically, it focuses on the role of Human-AI shared regulation in HI for learning and teaching. From this theoretical grounding, the article proposes the ontological foundations for Human-AI shared regulation in HI and discusses research propositions to guide future research in HI within IS, particularly concerning advanced technologies in learning and teaching.

Keywords: Hybrid Intelligence, Human-AI collaboration, Artificial Intelligence (AI), Self-regulated learning, shared regulation.

1. Introduction

The use of Artificial Intelligence (AI) in various societal domains, including learning and teaching, is not new. However, significant interest from practitioners and researchers has developed over the last decade. This interest has been greatly amplified following the public release of OpenAI's ChatGPT and the subsequent "technological races" among major technology companies to develop AI large language models, such as Google Gemini (formerly Bard), Meta's LLaMA, and Microsoft's Copilot. Information Systems (IS) researchers have explored the transformative impacts of AI advancements across different sectors, including supply chain management (Hendriksen, 2023), digital platforms (Wessel et al., 2024), digital marketing (Gupta et al., 2024), and IS education (Kishore et al., 2023; Van Slyke et al., 2023). Unlike previous technologies, recent advanced AI possesses the capability for highly interactive human interactions and the ability to adapt and learn from these interactions. This has led to growing interest in the concept of Hybrid Intelligence (HI) through human-AI collaboration.

Several definitions have been proposed for the term HI in IS and other disciplines (e.g., Dellermann et al., 2019; Järvelä et al., 2023; Molenaar, 2022; Moradi et al., 2019; Schmidt et al., 2022), yet HI broadly refers to the integration of human and artificial intelligences to achieve superior results and solve complex problems. Several propositions suggest that HI will be capable of solving problems and achieving outcomes that neither humans nor machines could achieve independently. In other words, researchers hope that HI will lead to outcomes where the combined capabilities of humans and AI produce results greater than the sum of their individual contributions, i.e., one plus one could be greater than two.

Although HI appears to be a promising domain for research and application, achieving true HI is far more complex than merely combining humans and AI. HI relies heavily on mutual understanding, effective interactions, dynamic adaptation, and both self- and shared regulation between humans and AI. The conceptual understanding of HI still remains quite limited.

The conceptualization of Hybrid Intelligence (HI) is further complicated by the bidirectional influences between humans and AI over time, during which they dynamically affect each other. Additionally, understanding HI becomes even more complex when examining interactions beyond one-to-one relationships, such as scenarios involving multiple humans and AI systems. Therefore, it is crucial to

URI: https://hdl.handle.net/10125/108842
978-0-9981331-8-8

establish a common understanding of the concept and systematically define the domain to both comprehend and advance hybrid intelligence.

In this paper, I first conceptualize Hybrid Intelligence (HI) and discuss it from various philosophical perspectives. I then shift our focus to human-AI shared regulation, proposed as the core process within HI. Using knowledge engineering and ontology-building methods, this study establishes the ontological foundations of human-AI shared regulation for hybrid intelligence. Finally, I discuss research propositions and implications.

2. Conceptual Foundations of Hybrid Intelligence

While most literature refers to Hybrid Intelligence (HI) as the integration of human and AI capabilities, views on how this integration should occur vary among different studies and philosophical perspectives. Despite these differences, these perspectives can be combined to inform the development of future HI systems, ranging from human-centred approaches to shared control and human-AI collaboration for HI.

2.1 Augmenting Human Intelligence with AI for Human-Centred Hybrid Intelligence

Rooted in the well-established domains of human-centred design for AI and technologies in general (Nguyen, Lämsä, et al., 2024; Shum et al., 2019), human-centred HI is one of the most popular concepts related to HI. From the perspective that technology should support and empower humans rather than replace them, several studies have emphasized that HI systems should be designed to augment human intelligence with AI. A scoping review by Hartikainen et al. (2024, p.163) of 23 academic papers on human-AI collaboration for HI in manufacturing highlights that HI "seeks to provide efficient solutions and positive outcomes for users and society, augmenting human abilities rather than replacing them." This perspective also suggests that HI systems should be designed to develop and enhance human abilities so that users retain the skills to perform tasks even if the technology is removed.

In the domain of learning and teaching, this aspect of HI is crucial because the primary goal is to equip students with essential skills and abilities. If cognitive AI were designed to replace certain thinking processes of learners, it could pose a risk by eventually diminishing their cognitive abilities. Therefore, it is essential to ensure that HI systems in education augment rather than replace learners' thinking and self-regulatory processes (Järvelä, Nguyen, & Hadwin, 2023).

Augmentation should focus on enhancing students' critical thinking, problem-solving, and creativity, providing tools that support and extend their natural cognitive abilities. For example, AI can offer personalized feedback, suggest resources tailored to individual learning styles, and facilitate collaborative learning environments where human and AI tutors work together to guide students. By integrating AI in a way that complements and enhances human cognition, HI can foster a more dynamic and interactive learning experience, encouraging students to engage deeply with the material and develop a stronger, more adaptable skill set. Additionally, HI systems should be designed to promote continuous learning and adaptability, enabling students to apply their skills in various contexts and adapt to new challenges as they arise. This approach not only preserves but also strengthens the learners' cognitive abilities, ensuring they remain active and engaged participants in their education.

Despite some controversial opinions, which are discussed later in this section, the essential agreement is that designing HI for positive outcomes for users, specifically students in learning and teaching context, and society is widely accepted.

2.2 Degrees of Automation and Control in Hybrid Intelligence

The degrees of automation and control in HI are pivotal in determining the effectiveness and safety of AI systems in various applications (Schmidt et al., 2022), including learning and teaching (Gašević et al., 2023; Molenaar, 2022a). Human oversight is a broad concept encompassing all levels of human involvement in AI systems, emphasizing the need for continuous human monitoring and control to ensure that AI operates within ethical and practical boundaries. Effective human oversight is crucial for preventing AI systems from making erroneous or harmful decisions and for maintaining trust in AI. In education, human oversight ensures that AI tools are used responsibly and that their integration into the learning environment enhances rather than detracts from the educational experience (Nguyen et al., 2023). The literature presents several concepts to describe different levels of human involvement in AI operations: human-in-the-loop, human-out-of-the-loop, human-over-the-loop, and human oversight.

Human-in-the-loop refers to systems where human intervention is necessary for decision-making processes. This model ensures that critical judgments benefit from human intuition and experience, which is particularly valuable in complex and ambiguous situations. Human-in-the-loop systems are common in educational settings, where AI tools assist teachers by providing data-driven insights, but the final decisions about student instruction and support remain with the educators. Related to human-centred HI, this human-in-the-loop approach ensures that AI augments rather than replaces human judgment, maintaining the teacher's role as the central figure in the learning process.

Conversely, human-out-of-the-loop systems operate with minimal or no human intervention, relying entirely on automated processes. These systems can perform tasks more efficiently at scale but raise significant concerns about accountability, ethical considerations, and the potential loss of essential human skills. In the context of education, fully autonomous AI systems might undermine the development of students' critical thinking and problem-solving abilities, as they might overly depend on AI for answers rather than engaging deeply with the learning material themselves. This is reflected in the main concern for human-centred HI. Nevertheless, human-out-of-the-loop is still necessary for processes that pose no potential risks to human development. It offers not only efficiency for individual personalized learning but also facilitates innovative adaptive approaches to enhance learning.

Human-over-the-loop represents a middle ground where humans monitor AI systems and intervene only when necessary. This model balances the efficiency of automation with the need for human oversight, ensuring that AI systems function correctly and ethically. In educational settings, teachers might oversee AI-driven personalized learning platforms, stepping in to adjust or guide the AI's recommendations as needed. This approach ensures that students benefit from tailored instruction without entirely removing human educators from the process.

The literature suggests that finding the right balance between automation and human control is essential for developing effective HI systems (Hartikainen et al., 2024; Molenaar, 2022a, 2022b). In the domain of learning and teaching, this balance is particularly critical. While AI can offer significant benefits by providing personalized learning experiences and supporting teachers, the degree of automation must be carefully managed to avoid diminishing the role of human educators and to ensure that students' cognitive abilities are augmented rather than replaced. Research highlights the importance of maintaining human involvement in AI systems to ensure ethical considerations are addressed, and educational outcomes are maximized (Nguyen et al., 2023). This ongoing dialogue in the literature draw attention to the need for a nuanced understanding of automation and control in HI, advocating for systems that leverage the strengths of both human and artificial intelligence.

2.3 Human-AI Collaboration for Hybrid Intelligence

The concept of human-AI collaboration for HI extends far beyond the mere distribution of labor between humans and machines. This collaboration seeks to harness the unique strengths of both parties, creating outcomes that surpass what either could achieve independently. The literature emphasizes that HI systems are designed to leverage the complementary capabilities of human cognitive skills and artificial intelligence, leading to a synergistic effect where the whole is greater than the sum of its parts.

Studies have shown that when humans and AI work together, they can tackle complex problems more effectively (Dellermann et al., 2019; Järvelä, Nguyen, & Hadwin, 2023). Human intuition, creativity, and contextual understanding combine with AI's data processing power, consistency, and speed, producing superior results. For instance, in educational settings, AI can analyze vast amounts of student performance data to identify patterns and provide personalized learning recommendations. At the same time, teachers can interpret these recommendations within the context of individual student needs and classroom dynamics, enhancing the overall educational experience.

Human-AI collaboration has been shown to enhance efficiency and effectiveness in various tasks (Järvelä, Nguyen, & Hadwin, 2023; Nguyen, Hong, et al., 2024). AI can automate routine and repetitive tasks, freeing humans to focus on more complex and creative activities. This not only increases overall productivity but also leads to higher job satisfaction and engagement, as humans are able to concentrate on work that leverages their unique skills and expertise.

However, achieving effective human-AI collaboration for HI requires careful consideration of the interaction dynamics between humans and AI systems. Designing interfaces and workflows that facilitate seamless communication and cooperation is essential for successful collaboration. This includes ensuring that AI systems are transparent and explainable (Lötsch et al., 2021; Nguyen et al., 2023), allowing humans to understand and trust AI-generated recommendations. Additionally, training and education for users are crucial to help them effectively interact with and leverage AI tools.

At the same time, aiming for successful yet equal collaboration between humans and AI raises several questions regarding fully human-centred HI, especially in learning and teaching. From a socio-technical perspective, living with technology in the age of AI is unavoidable in modern society. In the context of learning and teaching, Nguyen, Lämsä, et al. (2024) highlight that many learning activities and processes now incorporate technology, such as Google or Microsoft 365, extending beyond the classroom to include daily life tasks that are integral to self-regulated learning. This integration highlights the importance of designing HI systems that not only support educational outcomes but also align with the broader technological landscape that students navigate daily, both now and in their future careers.

3. Human-AI Shared Regulation for Hybrid Intelligence

Effective learning relies heavily on the development of self-regulation and shared regulation, both of which have been proven to be core skills (Dang et al., 2023; Malmberg et al., 2017). Individual self-regulation refers to a learner's ability to manage their own learning processes, including setting goals, monitoring progress, and adjusting strategies as needed (Bandura, 2001; Winne & Hadwin, 1998). Shared regulation, on the other hand, involves collaborative processes where regulation is distributed among group members, including AI systems (Järvelä, Nguyen, & Hadwin, 2023; Järvelä, Nguyen, Vuorenmaa, et al., 2023). For individual learners, self-regulation is essential for fostering independence and critical thinking skills. HI systems can support this by providing personalized feedback and adaptive learning paths that help learners reflect on their progress and make informed adjustments. For example, an AI tutor might offer hints or scaffolded support when a student is struggling, encouraging them to persist and find solutions on their own. This not only aids in immediate learning but also helps develop long-term self-regulation skills.

Advanced AI technologies, such as reinforcement learning, have demonstrated the capability to self-regulate by continually adjusting their models and improving performance based on feedback. This ability to self-regulate is crucial for HI systems as it enables AI to dynamically respond to changing conditions and optimize its support for human users. By incorporating these self-regulating AI models into HI systems, we can create a more adaptive and responsive learning environment.

Reinforcement learning, specifically, enhances these processes by allowing AI systems to learn from interactions and continuously improve their performance. This self-regulatory capacity of AI can be harnessed to refine the ways it supports both individual and group learning. For example, a reinforcement learning algorithm can optimize the timing and type of feedback it provides based on what has been most effective in similar situations. This creates a loop of continuous improvement, where the AI becomes better at supporting learning the more it interacts with users. Accordingly, Järvelä, Nguyen, and Hadwin (2023) has proposed a Human-AI shared regulation in learning (HASRL) model as shown in Figure 1.

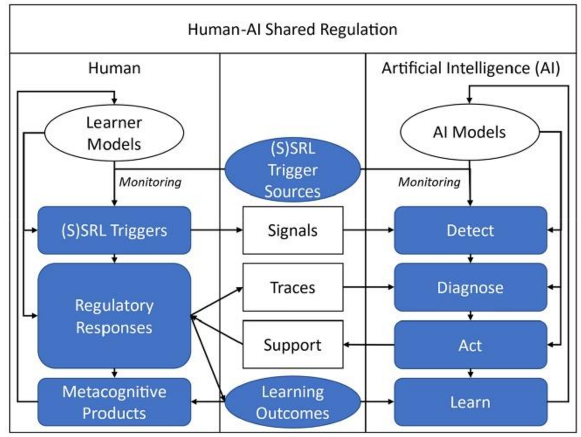

Figure 1: Human-AI shared regulation in learning (HASRL) model (Järvelä, Nguyen, & Hadwin, 2023)

Shared regulation among humans and AI extends the benefits of self-regulation to collaborative contexts. In group learning scenarios, AI can facilitate shared regulation by monitoring group dynamics, providing insights into group performance, and suggesting strategies to improve collaboration. For instance, an AI system could identify when a group is off-task and prompt them to refocus or highlight contributions from quieter members to ensure balanced participation. This level of shared regulation helps groups work more effectively together, leveraging both human and AI strengths.

4. Ontological Foundations of Human-AI Shared Regulation for Hybrid Intelligence

Individual regulation and shared regulation in collaborative learning are intricate and multifaceted concepts (Järvelä, Nguyen, & Hadwin, 2023). To guide the future design of Hybrid Intelligence (HI) systems that integrate the concept of human-AI shared regulation, this paper examines the primary ontological dimensions of human-AI shared regulation for HI, including types of regulation through social interactions, temporal levels of regulation in collaborative learning, and the primary facets of hybrid intelligence shared regulation.

4.1 Recognize Social Interactions for Regulation in Collaborative Learning

In the context of collaborative learning, social interactions both influence and are influenced by each individual in a group. Social interactions are recognized as a crucial factor contributing to the success of collaborative learning (Miyake & Kirschner, 2014). Recent advancements in learning sciences have emphasized the importance of social interactions in learning regulation, investigating social aspects of this regulation (Dang et al., 2023; Isohätälä et al., 2020). From social cognitive perspectives, social forms of self-regulated learning in collaborative learning have been theorized as co-regulated learning and socially shared regulation of learning (Hadwin et al., 2018). These forms focus on social interactions among learners, where they extend their thinking beyond individual capabilities to establish shared cognition. The evolving nature of these interactions presents challenges in measuring and augmenting human regulation in collaborative learning.

Adapting the socially shared regulated learning model (Järvelä & Hadwin, 2013), it can be argued that individual self-regulation, co-regulation, and shared regulation of learning influence and are influenced by each other throughout the learning processes. Individual self-regulation contributes not only to co-regulation among learners but also impacts shared regulation at the group level. Conversely, the regulation of collective activities affects individual thinking, goals, and performance, thereby modifying both self-regulation and co-regulation. Thus, examining regulation in collaborative learning necessitates a careful consideration of all three forms of regulation and their interrelationships. Research in this area should aim to identify the predominant form(s) of regulation in collaborative learning contexts, and the effects of social interactions on self-regulation, co-regulation, and shared regulation in collaborative learning should be thoroughly examined.

Integrating this discussion into the context of human-AI collaboration for HI, it is evident that similar principles apply. In HI systems, effective collaboration between humans and AI requires not just a distribution of labor but also an interaction that amplifies their combined capabilities. Social interactions within human-AI teams can enhance the regulation of learning by providing diverse perspectives and adaptive feedback mechanisms, much like collaborative learning among humans. The dynamic interplay between human cognition and AI capabilities can lead to superior outcomes, echoing the need for mutual influence and shared regulation observed in human-only collaborative settings.

As such, to optimize HI for learning, it is essential to design systems that support and enhance these interactive processes. This includes creating AI tools that are transparent, explainable, and capable of engaging in meaningful social interactions with human users. Furthermore, understanding the influence of these interactions on individual and collective learning processes can help in developing more effective HI systems that truly augment human intelligence. Therefore, examining social interactions and their regulatory effects within human-AI collaboration is crucial for advancing both collaborative learning and hybrid intelligence.

4.2 Recognize Temporal Levels of Regulation in Collaborative Learning

Regulation of learning is a cyclical process involving strategic and adaptive adjustments related to cognition, motivation, and emotions to overcome challenges and achieve learning goals. It encompasses both long-interval cycles of strategic changes (Caprara et al., 2008; Throndsen, 2011) and short-interval cycles of minor adaptations (Järvelä & Bannert, 2021). Research on learning regulation has explored changes in learning behaviors and strategies in self- and shared regulation as well as longitudinal changes in efficacy and beliefs (Schunk & Usher, 2011). Recent studies have also examined temporal regulatory processes and activities from a situative perspective of learning regulation (Dang et al., 2023; Järvelä, Nguyen, Vuorenmaa, et al., 2023). The regulatory cycles involve iterative refinements, where small-scale regulatory processes at shorter temporal levels are embedded within broader regulation of learning at higher temporal levels.

Considering the dynamic interactions among regulatory activities across different temporal levels (Järvelä & Bannert, 2021), it can be challenging to identify and measure regulation of learning. Table 1 lists the different regulatory focus corresponding to different timescales.

Table 1: Timescales for HI Shared Regulation

Timescale	*Orientation*	*Regulatory Focus*
Seconds	Immediate, Temporal	Regulatory triggers
Minutes	Event-oriented	Small-scale adaptive regulation
Days	Activity-oriented	Learning behaviour and strategies
Weeks	Curriculum-oriented	
Months	Criterion-referenced	Regulatory efficacy and beliefs
Years	Norm-referenced	

4.3 Primary Facets of Hybrid Intelligence Shared Regulation

Regulation in learning is a multifaceted construct that encompasses both affective and cognitive processes (Schunk & Greene, 2018). In his review, Panadero (2017) suggested that the three main facets of self-regulated learning activities are (meta)cognition, motivation, and emotion, as evidenced in various self-regulated learning models. Although these facets are interdependent and intertwined, identifying the primary regulatory facet(s) of interest is essential for selecting an appropriate theoretical framework to conceptualize and assess self- and shared regulation in collaborative learning.

Furthermore, specific data modalities are more closely associated with particular facets of learning regulation. Järvelä and Bannert (2021) have demonstrated how different data modalities can provide insights into the facets of learning regulation. For example, physiological data such as heart rate and electrodermal activity (EDA) are more indicative of emotional regulation processes than cognitive or motivational regulation. Conversely, eye gaze data are more useful for assessing learning attention, which reflects cognitive regulation. Thus, assessing regulation in collaborative learning involves identifying the relevant regulatory facet(s) of interest.

AI and other learning analytics systems can integrate multimodal data to provide a comprehensive understanding of specific facets of learning regulation (Järvelä, Nguyen, & Hadwin, 2023). For instance, cognitive regulation in collaborative learning can be investigated using log data to assess learners' actions and eye-tracking data to measure their attention. Additionally, data from different modalities can be combined to examine the interplay between (meta)cognitive, emotional, and motivational regulation.

Integrating these concepts into the context of Human-AI collaboration for HI, it is clear that similar principles apply. Effective HI systems require understanding and leveraging the multifaceted nature of learning regulation. In HI, AI can assist in monitoring and supporting various facets of learning regulation by analyzing multimodal data. For example, AI can track physiological signals to provide real-time feedback on emotional regulation or use eye-tracking data to offer insights into cognitive regulation.

5. Research Propositions and Implications

The integration of Human-AI shared regulation within HI systems presents significant opportunities for enhancing learning and teaching. As we explore this concept, it becomes crucial to identify key research propositions that can guide the development and implementation of these systems. This section aims to outline these research propositions and discuss their broader implications for the design and development of HI systems. By examining the theoretical underpinnings and practical applications of Human-AI shared regulation, we seek to provide a comprehensive framework that supports effective collaboration between human learners and AI, ultimately fostering more adaptive and personalized learning environments.

5.1 Considering Individual Self-Regulation and Shared Regulation among Humans and AI

HI systems should be designed to accommodate both individual self-regulation and shared regulation among humans and AI. Integrating both individual self-regulation and shared regulation within HI systems also addresses the complexity of learning in modern educational environments. Learners today often engage in both solitary and collaborative activities, and HI systems that can seamlessly support both contexts are more likely to be effective. By designing AI that understands and adapts to these dual modes of regulation, we can create learning environments that are both supportive and empowering.

Moreover, considering both forms of regulation ensures that HI systems do not inadvertently undermine human agency. When AI supports self-regulation, it helps learners become more autonomous and resilient. When AI participates in shared regulation, it enhances group functionality without taking over, maintaining a balance between human input and machine assistance. This careful integration is crucial for fostering a learning environment where both humans and AI contribute meaningfully and collaboratively.

Expanding the discussion to encompass collective HI, which involves the collaboration of many humans and many AIs, accentuates the importance of understanding how multiple entities can work together synergistically. Collective HI extends beyond individual and small group interactions to encompass larger, more complex systems where the collective efforts of humans and AI agents can lead to significant advancements and innovative solutions.

In such environments, the principles of individual self-regulation and shared regulation are amplified and require sophisticated coordination mechanisms. For instance, in a classroom setting where numerous students and AI tools interact, each student may benefit from personalized learning paths supported by AI, while collectively, the AI systems can analyse data across the entire class to identify trends, provide group-level insights, and suggest collaborative projects that align with the group's overall progress and needs.

Collective HI highlights the need for robust frameworks that facilitate effective human-AI collaboration on a larger scale. This includes the development of interfaces and protocols that allow for seamless communication and coordination among multiple AI systems and human users. It also necessitates the establishment of shared goals and metrics that guide the collective efforts of all participants, ensuring that the integration of AI enhances rather than hinders group dynamics.

5.2 Considering Short-term and Long-term Regulatory Processes for Hybrid Intelligence

In developing HI systems, it is crucial to account for both short-term and long-term regulatory processes of both human and AI. Focusing solely on immediate outcomes can lead to detrimental effects on human development over time. For instance, if an HI system is designed to take over certain cognitive tasks without fostering the underlying skills in humans, it may result in a gradual decline in joint performance in the long run. Therefore, an HI system must balance the immediate benefits of AI assistance with strategies that promote long-term cognitive growth and autonomy in humans.

Short-term regulatory processes often involve real-time adjustments and feedback mechanisms that enhance immediate task performance. These processes are vital for addressing current learning challenges and optimizing on-the-spot decision-making. However, overreliance on AI for these adjustments can reduce the opportunity for humans to develop critical self-regulation skills. Thus, HI systems should be designed to gradually transfer more responsibility to humans as their competence increases, ensuring they remain actively engaged in the regulatory processes.

In contrast, long-term regulatory processes involve sustained efforts to develop and refine skills over extended periods. For AI, this means incorporating self-regulation mechanisms that enable the system to learn from interactions and improve over time. For humans, long-term processes are about building deep understanding, critical thinking, and adaptive learning abilities. HI systems that support these long-term goals can help users develop resilience and adaptability, essential for thriving in an ever-changing technological landscape.

Moreover, considering long-term self- and shared regulation in AI models can optimize the overall benefits of HI systems. AI that continuously learns and adapts from its interactions with humans can provide increasingly personalized and effective support. This dynamic adaptation helps in maintaining a productive and supportive learning environment, ultimately leading to better outcomes for both humans and AI. By fostering a symbiotic relationship where both parties grow and benefit from the interaction, HI systems can achieve superior results that are sustainable over the long term.

5.3 Considering (Meta-)Cognition, Emotion, and Motivation for Hybrid Intelligence

The design of HI systems must take into account the interconnected aspects of (meta)cognition, emotion, and motivation in learners for effective learning and teaching. Contemporary research in psychology and neuroscience points out that cognitive and emotional processes are inseparable and intricately intertwined (e.g., Todd et al., 2020). Understanding this interplay is essential for designing HI systems that can truly enhance educational outcomes.

Cognition refers to the mental processes involved in acquiring knowledge and understanding through thought, experience, and the senses. Metacognition extends this concept by involving awareness and regulation of one's own learning processes. Emotion, on the other hand, encompasses the affective responses that can significantly influence learning. Motivation drives the engagement and persistence required to achieve learning goals. These elements do not operate in isolation but are dynamically connected, affecting how learners process information, retain knowledge, and apply skills.

For instance, positive emotions such as excitement and curiosity can enhance cognitive processes by increasing attention and engagement, thereby facilitating deeper learning. Conversely, negative emotions such as anxiety or frustration can impede cognitive functions, reducing the ability to concentrate and retain information. Similarly, motivation interacts with both cognition and emotion by providing the drive to initiate and sustain learning activities, which in turn can influence emotional states and cognitive performance.

HI systems that recognize and integrate these facets can offer more holistic and effective support for learners. For example, AI-driven tools can monitor emotional cues through physiological data, such as facial expressions or heart rate variability, and adapt the learning environment to reduce stress and increase engagement. Additionally, these systems can provide motivational feedback and challenges tailored to the learner's current state, fostering a more personalized and responsive educational experience.

Furthermore, incorporating (meta)cognition into HI systems allows learners to develop self-regulation skills. By tracking their own learning processes and receiving feedback, learners can become more aware of their strengths and weaknesses, enhancing their ability to control their cognitive strategies and emotional responses. This self-awareness is crucial for fostering independent, lifelong learning skills.

In practice, an HI system that integrates (meta)cognition, emotion, and motivation might present adaptive learning pathways that change in response to the learner's emotional state, cognitive progress, and motivational levels. For example, if a learner shows signs of frustration, the system could offer encouragement, adjust the difficulty of tasks, or suggest a short break. If a learner is highly engaged and motivated, the system could introduce more complex challenges to sustain their interest and cognitive growth.

The interdependence of cognitive and emotional processes suggests that any approach to enhancing learning through HI must be multifaceted, considering the whole learner rather than isolated aspects of their experience. By designing HI systems that reflect the complexity of human learning, educators can create environments that not only impart knowledge but also support the emotional and motivational well-being of students, leading to more profound and sustained educational outcomes.

Thus, integrating (meta)cognition, emotion, and motivation into HI systems is not just beneficial but essential. This approach ensures that learning is a comprehensive, engaging, and effective process, tailored to the nuanced and interwoven nature of human cognitive and emotional experiences. Contemporary insights from psychology and neuroscience provide a strong foundation for such integrated systems, promising a future where AI enhances education in profoundly meaningful ways.

5.4 AI Literacy for Hybrid Intelligence

A critical component of achieving effective Collective HI is fostering AI literacy among human participants. AI literacy involves understanding how AI systems operate, their capabilities, and limitations, as well as how to interact with and leverage these systems effectively. As AI becomes increasingly integrated into educational and professional environments, it is essential that individuals are equipped with the knowledge and skills to collaborate effectively with AI. With improved AI literacy, individuals can engage more confidently and competently with AI systems, leading to more effective and productive collaborations.

Promoting AI literacy can take several forms, such as incorporating AI education into school curricula, providing professional development opportunities focused on AI technologies, and creating resources that demystify AI for the general public. By enhancing AI literacy, we enable individuals to engage more confidently and competently with AI systems, leading to more effective and productive collaborations.

Moreover, AI literacy is crucial for addressing ethical considerations and ensuring responsible use of AI. As individuals become more knowledgeable about AI, they are better positioned to understand and question the decisions made by AI systems, advocate for transparency, and contribute to the development of ethical guidelines that govern AI use in collaborative settings.

In the context of Collective HI, where many humans and AIs work together, the importance of AI literacy becomes even more pronounced. Effective collaboration requires that all participants, human and artificial, are aligned in their understanding and use of AI tools. This alignment can lead to more innovative solutions, as humans are better able to leverage AI's strengths, and AI systems are designed to support and enhance human capabilities.

Furthermore, fostering a culture of continuous learning and adaptation is essential for sustaining Collective HI. As AI technologies evolve, so too must the skills and knowledge of human participants. This ongoing development ensures that the collaborative environment remains dynamic and responsive to new challenges and opportunities.

5.5 New Skills and Knowledge Demanded for Hybrid Intelligence

The advent of HI systems is redefining the skills and knowledge required in both workplace and educational settings. As AI systems become capable of taking over certain tasks, some current skills may become less critical, while new skillsets essential for effective collaboration with AI will emerge.

Current skills that could potentially be offloaded to AI include routine data analysis, basic administrative tasks, and certain aspects of decision-making processes that rely heavily on data-driven insights. AI's ability to process and analyze vast amounts of data more quickly and accurately than humans can make these tasks more efficient and reliable when handled by AI systems.

However, as these tasks are offloaded to AI, individuals will need to develop new skills to effectively work and learn alongside these intelligent systems. These new skillsets will likely include a deep understanding of AI's capabilities and limitations, enabling individuals to interpret and act on AI-generated insights appropriately. Critical thinking and problem-solving skills will become even more crucial as humans will need to make judgments on when to rely on AI and when human intervention is necessary.

Furthermore, individuals will need to acquire advanced digital literacy skills, encompassing the ability to navigate and utilize AI-integrated tools and platforms. This includes understanding how to configure AI systems, interpret their outputs, and provide meaningful feedback to improve their performance. Collaboration skills will also be vital, as effective human-AI interaction requires clear communication, coordination, and the ability to work seamlessly with AI as a team member.

Emotional intelligence and adaptability will be important as well, as individuals must navigate the ethical and social implications of working with AI. Understanding the impact of AI on their roles and being able to adapt to changes in the work environment will be critical for maintaining productivity and job satisfaction.

Future research should focus on identifying which current skills can be offloaded to AI and which new skills need to be promoted for effective human-AI collaboration. This involves investigating the specific tasks and functions that AI can perform more efficiently than humans and understanding the areas where human judgment, creativity, and emotional intelligence are irreplaceable. Research should also explore how educational and training programs can be designed to equip individuals with these new skillsets, ensuring they are prepared for the evolving demands of the workplace and learning environments driven by HI.

By anticipating these shifts and proactively addressing the need for new skills and knowledge, we can better prepare individuals for a future where HI systems play a central role in various aspects of work and learning. This approach will help maximize the benefits of HI while ensuring that humans remain essential contributors in an increasingly AI-driven world.

6. Conclusion and Final Remarks

Designing, developing, and implementing effective Hybrid Intelligence (HI) systems for learning and teaching is crucial to adequately equip young learners for a future workforce where AI is becoming an integral and inseparable part. In this paper, human-AI shared regulation is proposed as an essential element of HI. We have discussed the ontological foundations for human-AI shared regulation within the context of learning and teaching and have proposed several research propositions and implications for future research. This paper envisions that human-AI shared regulation for HI is essential for solving complex problems that neither humans nor AI could solve individually. By fostering HI, these systems incorporating human-AI shared regulation aim to enhance educational outcomes and prepare learners to tackle the multifaceted challenges of an AI-driven world.

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