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A Methodical Approach to AI-Supported Human Learning in Complex Task Environments

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ABSTRACT

Hybrid intelligence seeks to combine human and artificial intelligence so that their complementary strengths yield higher performance and continuous improvement on both sides, technical and human. However, in reality, AI systems in high-skill tasks often aim to optimize predictions and decisions, without producing learning opportunities and may even foster deskilling. This conceptual paper focuses on the human side of co-learning in hybrid intelligence and asks how AI can be designed to explicitly support human learning and upskilling in critical network operations. Building on the Supportive AI Framework, which provides learning support modes (transparency, exploration, animation, mirroring) that go beyond recommendation with explanation, we define learning targets in terms of macrocognitive skills. These targets are operationalized via Endsley's levels of situation awareness and decision making and structured according to Kolb's cycle of experiential learning. The paper outlines a theoretically grounded systematic design approach for developing AI functionalities that systematically foster human learning within hybrid intelligence settings.

Keywords: Hybrid intelligence, Supportive AI, Co-learning, Experiential learning, Situation awareness

INTRODUCTION

Hybrid intelligence aims to combine humans and AI based on their complementary strengths and weaknesses, with the goal of reaching better results than either could achieve on its own, and to continuously improve (Dellermann et al., 2019). To research hybrid intelligence is the aim of the HORIZON project AI4REALNET (cf. ai4realnet.eu), which develops AI-based solutions addressing critical networks (electricity, railway and air traffic management) that are traditionally operated by humans, and where AI systems complement and augment human abilities. In the project, continuous improvement of hybrid intelligence is considered in co-learning scenarios, which aim to enable humans and AI to learn from each other. However, to achieve true collaborative learning, collaboration between humans and AI must involve sophisticated design of learning processes on both the human

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and AI side (Holstein et al., 2020; van den Bosch et al., 2025; Van Zoelen et al., 2021). The AI4REALNET project designs, implements, and evaluates corresponding processes.

This is a conceptual paper that focuses on the human side of co-learning, that is, on how human learning can be specifically and systematically supported in settings of hybrid intelligence.

Most AI systems in high-skill tasks such as critical network operation are built to optimize predictions and decisions which are displayed on interfaces, often without explanations, but almost never with the aim of explicitly producing learning opportunities for humans (van den Bosch et al., 2025). In human-AI collaboration, where AI provides opaque recommendations for solving complex problems, human learning processes are not systematically supported. Similarly, students cannot learn to solve complex math problems if a teacher simply tells them the answer. Teachers rather need to enable students to understand the problem and to find ways to solve it. Accordingly, AI functions that are designed solely to solve a problem and not to support human problem-solving skills enable, at best, incidental learning on the part of humans and, at worst, are deskilling.

For critical network operation, the AI4REANET-project developed the *Supportive AI Framework* (Waefler et al., 2025; Leyli-abadi et al., 2025), which aims at an intensified human-AI collaboration (Waefler, 2021). This framework conceptualizes the human contribution to network resilience under complex, dynamic conditions as the abilities to monitor, detect, and understand situations and to make appropriate decisions based on explicit and tacit contextual knowledge. AI-supported human learning must specifically contribute to the continuous improvement of these capabilities.

Against this background, this paper elaborates AI functions for specific and systematic AI-enabled human learning in critical network operation. These functions are structured on the one side along Kolb's experiential learning cycle (Kolb & Kolb, 2009), and on the other side refer to Endsley's levels of situation awareness and decision-making (Endsley, 1995). The following two sections first describe the theoretical foundations for AI-assisted human learning. This is followed by an illustration of specific possibilities for AI assistance, using examples from the field of network operations.

THEORETICAL BACKGROUND

Specific AI functions designed explicitly and systematically to support human learning and upskilling for coping with complex decision-making situations, must relate to learning targets, learning processes, and appropriate modes of AI-support. The theoretical substantiation to which we refer regarding these three aspects is described below.

Learning Targets: Situation Awareness and Decision-Making

The Supportive AI Framework (Waefler et al., 2025; Leyli-abadi et al., 2025) conceptualizes human decision-making in critical network operations with reference to the concept of macrocognition (Klein et al., 2003; Klein, 2018), which explains the decision-making of human experts in high stakes real-life situations. Corresponding skills include the ability to understand situations, recognize critical developments, and cope with them appropriately, all based on explicit as well as tacit contextual knowledge in specific domains.

To derive learning targets related to these skills, we refer to Endsley's (1995) three levels of situation awareness as precursors to competent decision-making. Level 1 is perception, which requires knowledge of what the relevant situational cues are. Level 2 is comprehension, and thus, the ability to interpret information appropriately. Level 3 is projection and refers to the ability to anticipate further developments in the situation. Finally, decision-making includes knowledge regarding leverage points and coping strategies.

Learning Process: Experiential Human Learning

In order to identify specific ways in which AI can support the achievement of learning targets in macrocognition, as described above, we refer to Kolb's experiential learning cycle (Kolb & Kolb, 2009). This cycle describes how people acquire explicit as well as tacit knowledge based on concrete experiences. In detail, the cycle comprises four phases. It starts with phase 1, in which concrete experiences are gained in specific situations. This is followed by phase 2, where these experiences are specifically reflected upon in terms of their emergence, effects and interrelations. Phase 3 is about abstract conceptualization to integrate insights from phase 2 into one's mental models. Finally, in phase 4, the findings from the previous phases are tested through active experimentation and a next iteration of the learning cycle is initialized. Through such re-iterations, perceived signals become reflected insights, are generalized into rules, and are re-tested in practice or in simulation environments, enabling humans to continuously gain new concrete experiences.

AI-Support Modes: Beyond Recommendation

To support human learning in terms of decision-making in complex network operations, and thus to gain a deeper understanding of the network with its elements, interactions and processes, AI support must go beyond providing recommendations with or without explanations. Consequently, the Supportive AI Framework (Waefler et al., 2025) presents four different modes of human-AI interaction enabling far more AI functions than providing recommendations:

- Transparency [TP]: AI provides transparency regarding the learning content, e.g. by providing information or by explanation.
- Exploration [EX]: AI makes possible to explore the subject of learning, e.g. by simulation or by allowing to test different options.
- Animation [AM]: AI triggers reflection on the learning subject, e.g. by asking questions or by reporting anomalies.
- Mirroring [MR]: AI encourages self-reflection in human decision-makers, e.g. by reflecting behavioral patterns or individual decision-making styles.

CONCRETE AI-SUPPORT

The following four tables refer to Endsley's (1995) levels of situation awareness and to decision-making, and illustrate specific ways in which AI can support human learning. This distinction is made because there are specific ways in which AI can support learning in relevant cognitive processes. For each table a learning target is defined (e.g. improved perception for situation awareness level 1). To achieve these targets, the process follows the four phases of the experiential learning cycle: Concrete experience, reflection, abstract conceptualization, and active experimentation (Kolb & Kolb, 2009). For each of these phases, the tables contain generic descriptions of AI functions that are suitable for supporting human learning, based on the support modes transparency, exploration, animation, and mirroring (Waefler et al, 2025), illustrated by an example from network control. The tables are not intended to be exhaustive, but rather to provide structural aid for deriving corresponding AI-functions and to give concrete examples.

Table 1: Co-learning AI functionalities for situation awareness level 1: Perception.

	Generic AI-Functions	Specific Examples for AI Functions
	Learning Target: Improved Perception (Situation Awareness Level 1)	
Concrete experience	How might AI help humans experience their perceptual blind spots?	
	• Highlights anomalies [TP]	• Displaying heatmaps of potential conflicts in the network
	• Displays the current state of the system's behavior [TP]	• Marking emerging bottlenecks in the networks
	• Searches evidence for/against a human formulated hypothesis [EX]	• Providing evidence for/against humans' assumptions regarding critical spots in the network
Reflection	How might AI help humans reflect on what they noticed or missed, so they can better understand their own perception?	
	• Replay situations, so that humans can analyze their perception [TP; AM]	• Providing replays of conflicts in the network and highlighting potential cues.
	• Shows what the human looked at [MR]	• Displaying heatmaps showing the focal points of humans' attention in relation to cues
	• Compare human perception to AI detection [MR; AM]	• Providing comparison of humans' and AI detection cues in the network
Abstract Conceptualization	How might AI help humans abstract their observations into clear concepts, so they can generalize and reason better?	
	• Animating cue-rule generation [AM]	• The AI encourages the operator to formulate simple if-then rules from observed network patterns
	• Concept mapping of perceptual patterns [TP]	• The AI groups recurring signals or anomalies into clusters and visualizes them as network patterns

(Continued)

Table 1: Continued.

	Generic AI-Functions	Specific Examples for AI Functions
	Learning Target: Improved Perception (Situation Awareness Level 1)	
Active Experimentation	How might AI help humans run safe experiments with the system, so they can learn its dependencies and relationships and potential hotspots?	
	• Peer-perception comparison [AM; MR]	• The system visualizes attention heatmaps in the network from several operators, showing how experts scanned specific zones earlier
	• Safe exploration mode [EX]	• AI provides an exploration mode where new perception patterns can be applied in the network and tested in a safe environment

Table 2: Co-learning AI functionalities for situation awareness level 2: Comprehension.

	Generic AI-Functions	Specific Examples for AI-Functions
	Learning Target: Improved Comprehension (Situation Awareness Level 2)	
Concrete experience	How might AI help humans experience how elements/factors in the situation relate to each other?	
	• Relation mapping between system components [TP]	• The AI visualizes how current disruptions are interconnected within the network
	• Dynamic visualization of interdependencies [TP]	• Visualizes capacity dependencies in the network between sectors
Reflection	How might AI help humans reflect on their interpretations of the situation?	
	• Contrastive reasoning compares human vs. AI interpretation [TP; MR]	• Shows differences between humans' prioritizations within a network and the AI's suggested priority order, including explanations
	• Highlighting differences: Shows where interpretations differ from one another [TP]	• The AI visualizes sections of the network where human and AI interpretations diverge, e.g. areas the AI flags as stable while the human perceives instability.
Abstract Conceptualization	How might AI help humans abstract their comprehension into rules or models?	
	• Model synthesis: AI visualizes human-understood dependencies as system models (casual map) [TP]	• The AI generates a causal network map that visualizes how changes in one sector influence flows, loads, or signal states across connected nodes, helping the operator see system-wide relationships
	• Rule Comparison: Shows differences between human-defined rules and AI-defined rules [TP; MR]	• The AI compares human-created network rules (e.g., "If sector A is overloaded, reduce flow in B") with its own learned logic, highlighting overlaps, mismatches, and gaps in reasoning

(Continued)

Table 2: Continued.

	Generic AI-Functions	Specific Examples for AI-Functions
	Learning Target: Improved Comprehension (Situation Awareness Level 2)	
Active Experimentation	How might AI help humans test their understanding of the situation?	
	• Simulator for contrary interpretations [EX; AM]	• The AI lets the human test alternative interpretation of network behaviour and compares which interpretation best fits historical outcomes
	• Cue-Sensitivity Explorer [EX; TP]	• The AI allows the human to adjust the weight of different network cues to observe how the system's interpretation of the situation changes
	• Data-Reality Probe [TP; MR]	• The AI confronts the human's mental model with network data, highlighting where assumed dependencies align or conflict with actual system evidence

Table 3: Co-learning AI functionalities for situation awareness level 3: Projection.

	Generic AI-Functions	Examples for AI-Functions
	Learning Target: Improved Projection (Situation Awareness Level 3)	
Concrete experience	How might AI help humans experience how a current situation is likely to unfold before it happens?	
	• Visualization of emerging futures (branching timelines) [TP; EX]	• The AI visualizes multiple possible network states, showing how current flow or capacity trends could lead to stable or unstable conditions
	• Early-warning generation based on current trails [TP; AM]	• The AI continuously analyses real-time network trails to identify early patterns that typically precede critical slowdowns or overloads
Reflection	How might AI help humans reflect on the anticipated outcome?	
	• Comparison between expected and actual outcomes [TP; MR]	• The AI compares the human's predicted network state with the actual outcome, highlighting where and why projected flow, capacity, or stability levels diverged
	• Socratic prompting for reflective learning [AM; MR]	• The AI asks targeted questions such as "Which network indicators led you to expect this outcome?" to help the human reflect on the reasoning behind their projection

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Table 3: Continued.

	Generic AI-Functions	Examples for AI-Functions
	Learning Target: Improved Projection (Situation Awareness Level 3)	
Abstract Conceptualization	How might AI help humans abstract their projection into rules or models?	
	• Identification leading indicators of future trouble [TP]	• The AI analyzes network data to rank the signals and node parameters that most reliably predict a bottleneck within the next 10 minutes
	• Mirrors projection bias/error to humans [MR]	• The AI panel shows how optimistic or pessimistic operators are across network situations by visualizing gaps between predicted and actual outcomes
	• Captures how delays spread [TP]	• The AI panel maps and visualizes typical cascade paths within the network, showing how local disturbances evolve into broader effects
Active Experimentation	How might AI help humans test their projection strategies of the situation?	
	• Sandbox mode "what-if" [TP; EX]	• The AI provides a sandbox environment where operators can modify network parameters to explore how different strategies would change predicted outcomes without affecting live operations
	• Predicted vs. observed comparison [TP; MR]	• The AI compares predicted and actual network developments, visualizing which parameters or signals drove the deviation.

Table 4: Co-learning AI functionalities for decision-making.

	Generic AI-Functions	Examples for AI-Functions
	Learning Target: Improved Decision-Making	
Concrete experience	How might AI help people experience alternative decisions and their impact on outcomes?	
	• Real-time effects of decisions on the networks KPIs [TP; EX] • Impact transparency [TP]	• The AI visualizes in real time how different decision options affect key network indicators and KPIs • The AI makes visible which network areas are most affected by the human's current decision
Reflection	How might AI help humans reflect on their decisions they made?	
	• Comparison of decision-levers [TP; MR]	• The AI shows which network indicators, metrics, and recommendations the human considered when deciding and which were ignored, helping them reflect on how specific inputs influenced the chosen action
	• Decision rationale replay [MR]	• The AI replays the decision paths, highlighting moments of trade-offs (e.g. efficiency vs. resilience) and prompting reflection on the reasoning behind each choice

(Continued)

Table 4: Continued.

	Generic AI-Functions	Examples for AI-Functions
	Learning Target: Improved Decision-Making	
Abstract Conceptualization	How might AI help humans abstract their decisions into rules or models?	
	• Include decision principles from past cases [TP; EX]	• The AI auto-drafts an IF-THEN-UNLESS rule from similar successful network cases helping operators formalize effective decision principles
	• Mirrors operators tendencies/ biases in decision making [MR; AM]	• Highlights systematic priority for one or few service classes
Active Experimentation	How might AI help humans test their decision strategies?	
	• Impact feedback on KPIs and on sectors around [TP]	• The AI visualizes how each decision affects key network KPIs and shows the effects on surrounding sectors in real time
	• Sandbox mode "what-if" [EX]	• The AI allows operators to test decision A versus B in a simulated network environment and immediately see the impact on key performance indicators
	• Peer strategy suggestion [MR]	• The AI shows successful decision strategies from other operators in comparable network situations, encouraging experimentation with alternative approaches to improve outcomes

CONCLUSION

Co-learning is a prerequisite for the continuous mutual improvement in hybrid human-AI intelligence settings. Against this background, the present paper focuses on the human side of co-learning, that is., how AI can support human learning. We assume that AI that solves problems and makes suggestions to humans does not specifically and systematically support human learning. This is because humans normally do not understand AI-generated suggestions for complex problems and do not engage with related explanations (Endsley, 2023, Buçinca et al., 2024). We therefore propose identifying AI functions that specifically and purposefully support cognitive processes of human learning. To this end, we have developed a structuring aid that is based on the three levels of situation awareness and decision-making (Endsley, 1995), on the experiential learning cycle (Kolb & Kolb, 2009), as well as on the four different modes of AI-support for humans provided by the supportive-AI framework developed in the AI4REALNET project (Waefler et al., 2025). Applying this structuring aid resulted in a list of generic AI functions, as shown in the tables above. These go beyond current AI functions, which typically focus on the problem, and instead focus on the human problem solver. On this basis, the AI4REALNET project is developing concrete AI solutions and aims to achieve proof of concept in specific evaluation studies.

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