Human-AI Collaboration Types and Standard Tasks for Decision Support: Production System Configuration Use Case

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Abstract: Production systems can be considered as variable systems with dynamic structures and their efficient configuration requires support by AI. Human-AI collaborative systems seem to be a reasonable way of organizing such support. The paper studies collaborative decision support systems that can be considered as an implementation of the human-AI collaboration. It specifies collaboration and interaction types in decision support systems. Two collaboration types (namely, hybrid intelligence and operational collaboration) are considered in detail applied to the structural and dynamic production system configuration scenarios. Standard tasks for collaborative decision support that have to be solved in human-AI collaboration systems are defined based on these scenarios.

1 INTRODUCTION

Configuration of production systems is a complex task that cannot be done only manually and requires certain support (Järvenpää et al., 2019; Mykoniatis & Harris, 2021). Such systems can be considered as sets of resources that have some functionality and provide certain services. Services provided by one resource are consumed by other resources. Since the resources are numerous and with a changeable composition, production systems belong to the class of variable systems with dynamic structures. In some cases such systems can be controlled in a centralized way.

Traditionally, production system configuration has been solved in a two-stage fashion: (i) a structure of the system is formed at a strategic level (structural configuration) and (ii) its behavior is optimized at operational level based on actual demand and demand forecast (dynamic configuration).

Information technology has been employed to support configuration tasks for many years. The decision support system (DSS) incorporates information from the organization's database into an analytical network with the objective of easing and improving the decisions making.

Methods of collective intelligence (understood primarily as methods of humans working together to solve problems) and methods of artificial intelligence are two complementary (and, in some areas, competing) ways of decision support (Malone & Bernstein, 2022; Peeters et al., 2021; Suran et al., 2021). Usually, these approaches are seen as alternative (with some tasks being by their nature more friendly for methods of artificial intelligence, and others for those of collaborative intelligence). Presented here research intends to develop methods for the convergence of these two approaches and to build human-AI collaborative systems that can flexibly adapt to changes in the environment and the uncertainty and imprecision of the problem statement (through intensive collaboration between humans and AI agents), and also are of high scalability due to the use of software tools that implement AI models.

Potential (and existing) ways of convergence of collective intelligence and AI can be conditionally divided into two levels: basic and problem-oriented. The basic level includes processes that take place in a wide variety of systems in a wide range of applications, e.g., (Gavriushenko et al., 2020; Peeters et al., 2021). The problem-oriented level includes

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processes that require taking into account specifics of a particular application domain, e.g., (Bragilevsky & Bajic, 2020; Paschen et al., 2020). The paper focuses on the definition of collaboration and interaction types in DSS, and specify standard tasks for decision support in production system configuration scenarios as the use cases. Thus it tries to address the basic level generalizing conclusions obtained at the problem-oriented level. The contribution of the paper is the specification of collaboration and interaction types, as well as definition of standard tasks that have to be solved in human-AI collaboration systems.

The paper is structured as follows. Section 2 presents collaboration and interaction types derived based on the literature analysis. It is followed by a configuration case study examples used for extracting standard tasks arising during human-AI collaboration. The main results are summarized in the Conclusion section.

2 COLLABORATION IN HUMAN-AI DSSs

In this work, a collaborative DSS refers to a system in which multiple AI agents and humans collaborate to make a decision, with this the AI agents support humans and facilitate effective decision making and the agents and humans are mutually learn (Lee et al., 2021). Human-AI collaboration can be of various types. These collaboration types and types of interactions supporting the collaboration processes are outlined below.

2.1 Collaboration Types

The collaboration types are identified based on an anlysis of the research in which different collaboration levels between AI agents and between AI agents and humans are described. In the present research, these levels are investigated from the perspective of the goals of collaboration partners, the strategy for achieving the collaboration goal, the principles of divisions of labour between the partners, and the learning opportunities.

Collaboration supposes that partners interact to achieve the shared common goal. In the present reseach, this goal is the goal of the collaboration or a decision. At that, each partner can pursue the individual goals. The research considers individual goals as kinds of activities for which a partner is responsible in the process of the general goal achievement. Different collaboration types address the relationship between the general and individual goals differently. This paper distinguishes two sorts of relation to the goal: individual (for the activities contributing to achieving the common goal) and general (for the activities prevailing over individual interests).

The strategy for achieving the collaboration goal is a manner of the partners' behaviors (actions). This manner can be a reaction in response to some events after they occur, or the behavior when the partner is the initiator of the actions, anticipates the effects on themselves and develops the necessary reactions from other partners. The former manner is referred as a reactive strategy, the latter as a proactive one.

The division of labour is the way of assignment of activities to the partners, that to be carried out to achieve the collaboration goal. Fixed and situational divisions are distinguished. The fixed division is based on the competency needed in the assigned activities. With this way, each partner focuses on a narrow set of activities they are distinctively good at, or are specialists. The situational division suggests that the partners in response to the situation agree among themselves who performs what kinds of activities. This way assumes that there may not be specialists in all the required activities.

The learning opportunities is an indicator of whether AI and human can learn in the collaboration process, and, if so, what form of learning is supported. Three forms of learning are considered: 1) unidirectional when human trains AI; 2) unidirectional when human teaches human; 3) bidirectional when human and AI mutually learn.

Table 1 summarizes the collaboration types identified from the perspectives of the partners' relation to the goal, the manner of the partners' actions, the division of labour, and the learning opportunities.

Responsive collaboration (Crowley et al., 2022) is a form of tightly-coupled interaction where the actions of each agent are immediately sensed and used to trigger actions by the other. Even a small lag in responsiveness can have serious undesirable consequences (for instance, a delay in informing about the danger of encountering an obstacle to avoid a collision when driving a car). The responsive collaboration suggests that each partner pursues the individual goals and carries out activities of their competence scope. The dependence of the actions of a partner on the the actions of another partner, means a reactive strategy of the goal achievement. Learning in the responsive collaboration is about AI learning to convert perception signals directly into motor commands or actions in order to tune AI to the sensorimotor reflexes of the human partner.

Table 1: Collaboration types.

Collaboration type	Goal	Strategy of goal achievement	Division of activities	Learning
Responsive	Individual	Reactive	Fixed	Unidirectional: human trains AI
Situational	Individual	Reactive	Situational	Unidirectional: human trains AI
Deliberative	Individual	Proactive	Fixed	Not supposed
Praxical	Individual	Proactive	Fixed	Unidirectional: human trains AI, human teach human
Delegation	General	Reactive	Situational	Unidirectional: human trains AI
Hybrid intelligence	General	Proactive	Fixed	Mutual: human-AI
Human-in-the-loop	General	Proactive	Fixed	Unidirectional: human trains AI
Operational	General	Proactive	Situational	Unidirectional: human trains AI, human teach human
Creative	General	Proactive	Situational	Mutual: human-AI

Situational collaboration (Crowley et al., 2022) refers to a model where perception and actions are mediated by shared awareness of situation and the partners' actions are their response to the situation. As follows from the definition, the situational collaboration supposes a situational division of activities, where each partner pursues the individual goals; is supported by a reactive strategy because the actions of the partners are situation responsive; and requires AI to learn to perceive the situation.

Deliberative collaboration (Nakahashi & Yamada, 2021; van den Bosch & Bronkhorst, 2018) is a model where the partners synthesize a collaborative plan that defines activities to be performed by human and AI. The partners exchange the information on the individual goals to built the plan and stick the proactive strategy of the goal achievement. The fixed plan has a fixed division of the activities as a consequence. This collaboration type does not supposes any learning activities.

Praxical collaboration (Crowley et al., 2022) involves the exchange of knowledge about how to act to achieve the goal, acquired as a result of experience or training. In this collaboration, each action is due to both the previous action and the expected result from the partner, which means that the partners follow the proactive strategy. The exchange of experience / training knowledge gives evidence of mutual learning of the partners where one kind of the partners fulfills the role of teacher, and the other takes the role of a trainee. Such division of roles assumes that a fixed division of activities takes place. Exchanging the knowledge, the partners aim at the individual goals.

Delegation (Candrian & Scherer, 2022; Fuegener et al., 2022; Lai et al., 2022) is a model when a preplanning of the parter activities is not supposed; the partners delegate activities each other in the process of the goal achievement. The delegation supposes that the partners share a common goal without a fixed divisions of activities. This type of collaboration supports the proactive strategy because the partners react to the commands from each other in the delegating process. The delegation can involve activities on AI learning from human if one of the partners delegates such activity to human.

Hybrid intelligence (Demartini et al., 2020; Hemmer et al., 2022; Hooshangi & Sibdari, 2022) is a way for humans and AI to collaborate where they extend and supplement strengths of each other, and where each partner contributes to the goal. With hybrid intelligence, human learns from AI and benefits by generating new knowledge, and in return transfers implicit knowledge from human opinions to enrich the AI performance. Here, the partners share the common goal and follow the proactive strategy to achieve it. This collaboration supposes a fixed division of activities according to the partner competencies. In the collaboration process, the AIs inform human about the results of their activities, and human transfers them the implicit knowledge, which ensures mutual learning of the partners.

Human-in-the-loop (Demartini et al., 2020; Hooshangi & Sibdari, 2022) is a model that requires human involvement in the collaboration. This type of collaboration aims at leveraging the ability of AI to scale the processing to very large amounts of data while relying on human intelligence to perform very complex tasks. Human in the loop is similar to the hybrid intelligence except the former supposes unidirectional learning model when human trains the AI and transfers to the AI the implicit knowledge.

Operational collaboration (Crowley et al., 2022; van den Bosch & Bronkhorst, 2018) is a model when the partners exchange information on the current and desired situations, their expression as intentions, goals and sub-goals, tasks and sub-tasks, and plans of actions that can be used to attain the desired situation. This type of collaboration can also concern actions that can be used to attain or maintain a stable situation as well as detection of threats and opportunities. The operational collaboration is used in complex systems where parallel processes (executive and interactive) take place, many collaborators are involved, and decision support concerns planning joint actions and putting them into operation. Such a collaboration supposes that the partners share the common goal and follow the proactive strategy. The division of activities is situational. The operational collaboration suggests learning AI from human, and mutual learning of humans from each others as a parallel process during planning and acting.

Creative collaboration (Crowley et al., 2022) refers to a model where AI and human work together to solve a problem or create an original artefact and where each partner improves and builds on the ideas of the others. Here the partners share a common goal and follow the proactive strategy of the goal achievement. The division of activities is of the situational nature. Collaborating, the partners exchange ideas and hypothesis how to achieve the goal, mutually enrich each other's ideas and, accordingly, mutually learn.

2.2 Interaction Types

To collaborate, partners need to interact. Types of interactions between AI and human are adopted from the taxonomy of design knowledge for hybrid intelligence systems (Dellermann et al., 2019) and the research on cooperation of humans and AIs in complex domains (van den Bosch & Bronkhorst, 2018). The referred works specify the interaction types as explained below.

Interactions from AI to human:

- Resulting: for humans, AIs are black boxes that present outcomes of their activities without any explanations;
- Explainable: AIs present outcomes and the process resulting in them (explanations), human understands how AI has produced an outcome;
- Informing: an AI initiates interaction and can voluntarily (without human requests) provide information (e.g., detecting misunderstandings, possible errors of judgment, etc.)

Interactions from human to AI:

- Request: human intiates interaction and requests explanations from the AI on demand. The initiative for clarification lies on the part of the human, and requires from the AI the capability to determine the purpose of the human's request, and to select and generate explanations that fit the purpose (query-based explanations);
- Learning AI: human trains AI model.

In the paper, the interactions types above are classified as follows.

Interactions initiated by an AI:

- Informing: an AI presents to human information, which can be accompanied by appropriate explanations, without any request from the human part.

Interactions initiated by human:

- From human to AI: request, learning AI;
- From AI to human: resulting, explainable as response to the human request;

Several types of interactions can occur in the same collaboration scenario.

3 HUMAN-AI COLLABORATION SCENARIOS AND STANDARD TASKS

Production system configuration is considered as a use case for AI-human collaboration and deriving standard collaboration tasks.

Decision support in the area of production system configuration is characterized by the common goal for collaboration partners. It also assumes hard division of activities in accordance to the competencies of the collaborating parties. As a result, the hybrid intelligence is chosen as the most appropriate collaboration type for structural production system configuration scenarios.

Successful dynamic production system configuration heavily depends on the analysis of contextual information and assumes situational division of activities. The operational collaboration most fully meets the requirements from the scenario of dynamic production system configuration and therefore is chosen for this case.

The developed scenarios are described in tables 2, 3 and illustrated in fig. 1, 2 as sequences of stages, corresponding interaction types, and standard tasks to be solved. AIs are represented as agents with names reflecting their functionalities.

One can see that the main difference in the considered production system configuration scenarios is centralized (in the hybrid intelligence collaboration) and decentralized (in the operational collaboration) problem solving planning. It can be interpreted as in structural production system configuration the problem solving is better planned but slower, whereas solving the dynamic production system configuration problem is performed faster but assumes ad-hoc configuration and usage of the contextual information.

Below the specified standard tasks are described.

Organizing of the information exchange between the partners of the collaborative DSS. The task arises in situations where it is necessary to organize the exchange of information directly between collaborating partners or through the publication of information in the smart space (common information space providing infrastructure for efficient partner interactions). To solve this task a form of information representation that would be understandable to all the partners as well as methods for information exchange and information access are required.

Table 2: Structural production system configuration scenario based on the hybrid intelligence collaboration type.

Stage no.	Stage description	Interaction type	Standard task
1.	Decision maker describes the structural production system configuration problem in a partially formalized way.	Informing	Organization of information exchange between the partners of the collaborative DSS
2.	Translation agent translates the structural production system configuration problem description using ontology	Request or informing	Translation of the request to the ontology-based description
3.	Translation agent delivers the translated problem description to the decision maker with explanations of the translation.	Explainable	Ontology-based explanation of the AI agent actions
4.	The decision maker checks if the translated request is correct. If the decision maker is not satisfied with the translation result, the translation agent is to be trained.	Learning AI	Training of the AI agent based on human feedback
5.	The planning agent identifies the activities that need to be accomplished to achieve the goal of the collaboration (decision maker's problem solving) and creates a work plan that specifies a) which works the agents have to perform and which works are to be performed by humans, and b) for activities the agents must provide explanations of how the results are achieved.	Request (or informing) and resulting	Planning the problem solving process (centralized)
6.	Publishing the problem description in the smart space (description in natural language for humans and translated description for humans and agents) and the plan of problem solving.	Informing	Organization of information exchange between the partners of the collaborative DSS
7.	Potential partners (agents and humans able to access to the smart space) announce their willingness to participate in the problem solving	Informing	Collaborative DSS team formation
8.	The competence agent checks potential DSS team partners for the competencies required to perform their chosen activities, delivers the results of the check to potential partners, and allows/forbids them to participate in the problem solving in accordance with the implemented mechanism for recruiting partners to the team. The invitation/rejection for a potential human partner is accompanied by an explanation	Resulting (or explainable) and informing	Collaborative DSS team formation
9.	Problem solving. Partners who have completed their activities informed all other team members or following according to the plan team members, depending on implementation) and, when planned, provide the explanation.	Informing and explainable	a) Organizing of the information exchange between the collaborative DSS team partners b) Ontology-based explanation of the AI agent actions
10.	DSS agent delivers the set of results to the decision maker	Explainable	a) Ontology-based explanation of AI agent actions b) Human learning based on the explanations of the AI agent

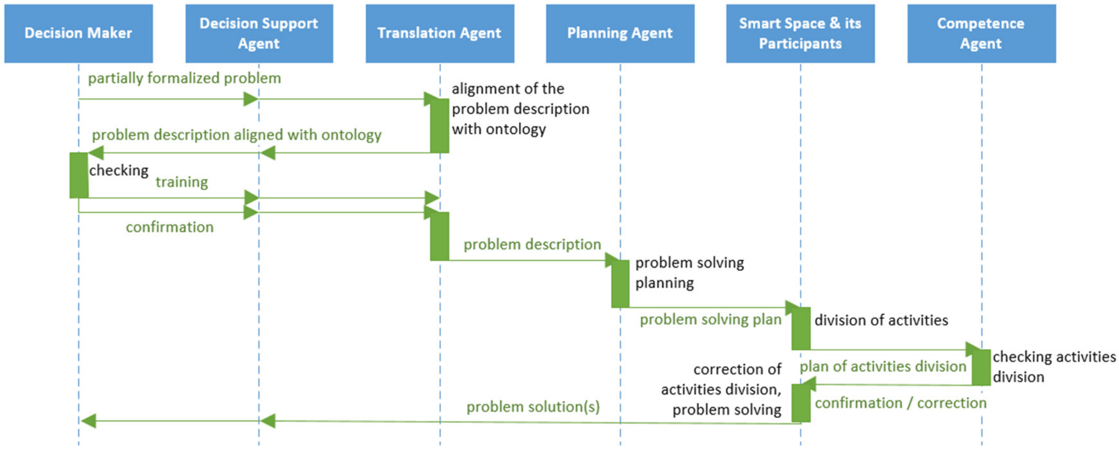

Figure 1: Sequence diagram of structural production system configuration scenario based on the hybrid intelligence collaboration type.

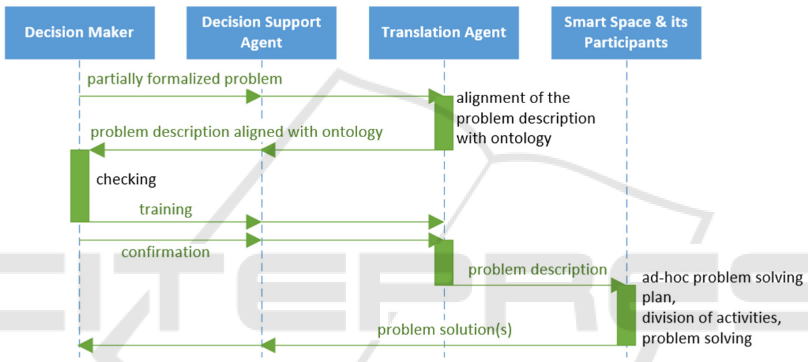

Figure 2: Sequence diagram of dynamic production system configuration scenario based on the operational intelligence collaboration type.

Translation of the request to the ontology-based description. The task is associated with the representation of the problem, the decision for which is the collaboration goal, in a form understandable to humans and AI agents and allowing to ensure their interoperability. Ontologies are generally accepted means to organize such a representation. To solve the task, it is proposed to represent the problem, formulated in the request, by ontology means.

Ontology-based explanation of the AI agent actions. The solution of this task aims at developing a way for the AI agent to produce the result in a human-understandable form. Since partners' interoperability (their ability to interact functionally) is supported by an ontology, it is natural to suggest the same form for presenting explanations of the functions (works, results) performed by the AI.

Planning the problem solving process. The task is aimed at creating a plan for solving the problem by the collaboration partners. Depending on the nature of division of activities between the partners, this task can be solved in a centralized or decentralized way. The centralized method implies the presence of the partner responsible for planning in the DSS. In the scenarios under consideration, this role is assigned to a planning agent in the hybrid intelligence scenario. Decentralized method implies solving the planning problem through negotiations between the partners, which corresponds to stage 6 of the operational collaboration scenario. Such a method has been presented in (Smirnov & Ponomarev, 2021).

Collaborative DSS team formation. To solve the task, it is required to choose or develop a mechanism that enables formation of an efficient team. The effectiveness of a team may be affected by the number of its partners, division of activities between them, their workload, qualifications, and other indicators. The proposed set of indicators should be the basis of the selected or proposed mechanism for forming the human-AI team.

Training of the AI agent based on human feedback. The emergence of the task is a human response to the actions of the AI agent, which the human learns about during informing, resulting, or

Table 3: Dynamic production system configuration scenario based on the operational collaboration type.

Stage no.	Stage description	Interaction type	Standard task
1.	Decision maker describes the problem of dynamic production system configuration in a partially formalized way.	Informing	Organization of information exchange between the partners of the collaborative DSS
2.	Translation agent translates the structural production system configuration problem description using ontology	Request or informing	Translation of the request to the ontology-based description
3.	Translation agent delivers the translated problem description to the decision maker with explanations of the translation.	Explainable	Ontology-based explanation of the AI agent actions
4.	The decision maker checks if the translated request is correct. If the decision maker is not satisfied with the translation result, the translation agent is to be trained.	Learning AI	Training of the AI agent based on human feedback
5.	Publishing the problem description in the smart space (description in natural language for humans and translated description for humans and agents) and the plan of problem solving.	Informing	Organization of information exchange between the partners of the collaborative DSS
6.	Potential DSS team partners (agents and humans) develop a common plan of work based on the information exchange concerning, collaboration goal, intentions, tasks, context, and work plans for problem solving	Informing and explainable	a) Collaborative DSS team formation b) Planning the problem solving process (decentralized)
7.	Problem solving. Partners exchange their statuses and inform other partners upon completion of their tasks	Informing and resulting	Organizing of the information exchange between the collaborative DSS team partners
8.	DSS agent delivers the set of results to the decision maker	Explainable	a) Ontology-based explanation of AI work b) Human learning based on the explanations of the AI agent

explainable interactions. As a rule, this task arises when it is necessary to refine the AI model (for example, if the existing model gives wrong results). The problem requires the selection or development of a learning model, as well as the development of interfaces for organizing feedback and for the learning process.

Human learning based on the explanations of the AI agent. This task is a consequence of solving the problem of ontology-based explaining the actions by the AI agent. If human learns something new from the explanations received, s/he is considered to have gained new knowledge or experience; that is the AI agent taught him something. Note: another consequence of the task of ontology-based explaining the actions of the AI agent is that the person understands that the agent works correctly (incorrectly); this consequence does not lead to the acquisition of new knowledge by the human.

4 CONCLUSIONS

The paper considers collaboration in human-AI collaborative decision support systems via a use case of production system configuration. Nine collaboration types are defined from the perspectives of the partners' relation to the goal, the manner of the partners' actions, the division of labour, and the learning opportunities. Based on the direction of interactions between human and AI, and the nature of the exchanged information and knowledge, five interaction types are defined.

The problems of structural and dynamic production system configuration are considered as case studies. It is shown that hybrid intelligence is the most suitable collaboration type for structural production system configuration (since it is characterized by the common goal for collaboration partners and assumes hard division of activities in accordance to the competencies of the collaborating parties), and the operational configuration the most suitable for the dynamic production system configuration (since it heavily depends on the analysis of contextual information).

Based on the case study analysis, seven standard tasks that have to be solved in human-AI collaboration processes are defined together with their specifics and ways of solving.

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