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Co-creation Design Patterns for Human-AI Teaming in Manufacturing and Multi-Domain Decision-Making

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Abstract: This paper presents a co-creative methodology for the design of human-AI teaming in decision-making for dynamic environments, introducing a range of human-AI teaming design patterns, applicable to diverse domains. The methodology integrates aspects of systems design and enriches them with a typology of human-AI teaming in decision-making. It engages stakeholders in decision-making processes for the joint identification of decisions, targets, success metrics, and associated risks. This is enabled by co-creation design patterns, as part of an agile methodology that includes iterative cycles of physical and virtual collaboration, as well as synchronous and asynchronous activities between parties involved in the design, development, testing, and use of the system. The methodology is applied in a multiple case study and lessons from a manufacturing case are presented from the first phase of implementing the methodology.

Keywords: AI decision making; Human – AI teaming; human-centric AI; co-creation.

1. INTRODUCTION

Incorporating Artificial Intelligence (AI) in complex and dynamic environments reshapes many decision-making processes. This comes with enormous advantages but also risks. Guidance about identifying and managing such risks is provided through relevant international standards (ISO, 2023; NIST, 2023), and regulations are targeting the harmonisation of standards and rules for AI applications and use (Regulation (EU) 2024/1689, 2024). This has led to complementing earlier recommended practices regarding ethically aligned designs for intelligent systems (IEEE, 2017) through the introduction of new standards to establish safeguards and controls for automated AI systems (ISO/IEC TS 8200, 2024). Nonetheless, AI-enabled decision processes increasingly do not simply follow unidirectional patterns where AI is seen as a decision aid or human augmentation tool (Leyer & Schneider, 2021; Raisch & Krakowski, 2020). Instead, humans work with AI in increasingly complex and iterative ways (Steyvers & Kumar, 2023) and the human-AI teaming outcomes exhibit emergent properties, significantly expanding the capabilities of humans and AI acting alone (Emmanouilidis et al., 2021). What is clear among all such developments is that the design and operation of AI-enabled systems and processes cannot simply rest on isolated input from designers, developers, and operators of AI-enabled systems. Instead, a multi-stakeholder approach is needed that integrates diverse concerns and knowledge. Participatory design and stakeholder deliberation are a promising way of ensuring such multi-stakeholder viewpoints (Zhang et al., 2023). Participants can contribute effectively to the design of AI-driven decision-making tools using web-based and virtual collaboration tools. Yet, the way humans and AI can collaborate in decision-making is still not sufficiently understood and, therefore, such design processes can be ineffective. Involving re-usable common design patterns has long been sought in engineering systems design (Gamma, 1994), but such patterns are not well established for human-AI teaming in decision-making. Therefore, design collaborating teams are not sufficiently aware of the design space options (Tsiakas & Murray-Rust, 2024). Equipping such teams with concrete design patterns for human-AI teaming is seen as a significant scaffolding mechanism for making the co-creation of human-AI interaction more effective (Yildirim et al., 2023).

This paper introduces a co-creative approach based on human-AI teaming design patterns tailored to human-centric AI-enabled decision-making systems with explicit consideration of multi-stakeholder teams, human-AI teaming types, and related decision risks. This is an evolved and expanded version of an earlier methodology (Waschull & Emmanouilidis, 2022) targeting AI-driven decision-making through iterative cycles of physical and virtual collaboration, as well as synchronous and asynchronous activities between stakeholders involved in the design and use of decision systems. The methodology is applied in a multiple case study involving multi-domain AI decision-making, with details from the application on a manufacturing use case presented in this paper. The paper is structured as follows. Section 2 introduces the typology of human-AI teaming in AI-driven decision systems, proposing a broad perspective beyond human augmentation vs automation and human replacement. The typology is relevant for the role and agency of humans in AI-enabled decision-making processes. Section 3 introduces the co-creation methodology and the human-AI teaming design patterns. Section 4 outlines the methodology implementation, while lessons learned from implementing its first phase are discussed in Section 5.

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2. HUMAN-AI TEAMING IN DECISION MAKING

Decision-making driven by AI typically aims to bring operational benefits, for example, higher effectiveness and efficiency of processes or operations in a given domain. This is aimed to be achieved through more accurate and timely decisions, which are better informed by available evidence and are grounded in sound domain knowledge. When AI-enabled decision-making is applied in complex and dynamic environments, understanding the typology of Human-AI teaming within decision–making becomes essential. A typical view is to distinguish between *decision-support* and *decision-making* systems, depending on whether AI is used as an aid or as an automation mechanism for decisions. Depending on the level of human involvement in AI-enabled decision-making, the decision can be taken by humans with AI recommendations (*human-in-the-loop*), or be automated but with clear human overriding authority and role (*human-on-the-loop*), or automated without human involvement (*human-off-the-loop*) (Ivanov, 2023). In human-on-the-loop approaches, human agency might become less effective, potentially diminishing influence over algorithmic decision systems (Koeszegi, 2023).

The human-in-the-loop and human-on-the-loop concepts may encompass the capability for human intervention in every decision cycle of a system. The human-on-the-loop involves the capability for human intervention during the design cycle of the system and human monitoring of the system's operation, and a human-in-command concept is proposed to imply the capability to oversee the overall system activity and determine how and when to use it, including the authority to override any decisions (Aschenbrenner et al., 2024). Nonetheless, there are limitations even in such a viewpoint, as the capability of humans to react to events and appropriately determine in real-time when a decision should be made by a human or an automated AI-enabled agent is limited. Therefore, agent-based mechanisms for sliding autonomy in decision-making and control have been proposed (Frasheri et al., 2022). Such approaches still have challenges, and the view from various literature works could be seen as converging to include:

- High complexity of relevant socio-technical and socio-economic systems
- High variability in factors and phenomena affecting decision-making
- High uncertainty regarding the overall context and environment of decision-making
- High number of stakeholders involved in decision-making
- High level of ambiguity in the perception of phenomena feeding into the decision-making (contested facts/inputs)
- High level of conflict between the interests of involved stakeholders
- High level of unbalance between decision actors (e.g. weak actors, equity issues) in value-led decisions
- Decision success rests highly on coordination among multiple stakeholders
- Decisions involving stakeholders of sufficient power, making negotiation necessary

Such challenges can be looked upon differently, beyond just looking at the level of automation or the level of human agency and control. While these remain fundamentally important, such a 'linear' (the term 'linear' here is intended to capture a presumed linear scale of AI automation or human agency and control) view is insufficient to capture the deeper engagement of humans with AI. An expanded view also considers *decision collaboration* and *decision innovation* systems (Storey et al., 2024). Decision collaboration involves two-way synergies between humans and AI, including mutual learning and verification, and several interaction cycles. Even if the decision agency is assigned to one of the two actors at the end of the process, the decision ceases to be attributable to either one of the two alone. Decision innovation takes the process even further, shaping a creative environment equipped with methods and tools that unleash more creative and imaginative decision options. Neither decision collaboration, nor decision innovation fit within the linear space that lies between fully manual (human-only), augmented (human-aided by AI), or fully automated (AI-only) options (Raisch & Krakowski, 2021). Therefore, human-AI decision-making design spaces need to be seen from a broader perspective.

The emerging new design space for human-AI teaming in decision-making is relevant to three different design pillars, namely technical (e.g. AI, automation, robotics), socio-technical (e.g. human-AI teaming), and social (e.g. human collaboration, behaviour, monitoring and oversight) (Storey et al., 2024). Extending this view, and building on the categorisation of human-AI teaming in decision-making mentioned earlier in this section, human-AI collaboration types can be further distinguished as follows:

(A) Human always makes the decision without AI
Relies on human analytical capabilities and intuition.

(B) Decision Support System (human always decides)
B.1. AI analyses, human decides, acts
B.2. AI offers options, human analyses, decides, acts
B.3. AI recommends action, human analyses, approves or rejects action and takes another action.
There are 2 variations of B.1, B.2 and B.3:
V1: AI does not learn from or is aided by the human. Here, the AI is pre-trained, pre-designed, or trained/designed outside the interaction with the human decision-maker. Non-decision-maker humans may be involved in preparing/setting up the AI system.
V2. AI learns or is aided by the human decision-maker. In this case, a human offers feedback to AI (explicit feedback) or AI learns from the human decisions and actions (implicit). Humans are involved in preparing/setting up the AI system.
Configuration referred to as B.1/V1 B.1/V2 etc.

(C) Decision System - Automated
Automated decisions with human in- or off-the-loop
C.1. AI takes action, human is not involved
C.2. AI notifies the human of imminent action, human overrides/vetoes action
C.3. AI takes action and informs human, human interrupts/suspends/cancels action

(D) Decision System – Joint Action by Humans – AI team

D. Human develops candidate decisions by interacting with AI and selecting one.

There are 2 variations of C.1, C.2, C.3, and D, (V1,V2), the same as for B.1, B.2, B.3, depending on how AI learns. The above evolves the typology in (Emmanouilidis et al., 2025) and is linked here with co-creation design patterns, introduced in the next section, extending a previously proposed methodology from Waschull and Emmanouilidis (2022).

3. CO-CREATION DESIGN AND PATTERNS

Decision-making in diverse domains may involve different stakeholders, aims, and often processes. However, common reusable patterns may encapsulate the needs of these varied domains. This idea was explored by assessing the design space for human-AI teaming in decision-making for a collaborative research project, which aims to deliver methods and tools for hybrid human-AI decision support for enhanced human empowerment in dynamic situations (humaine-horizon.eu). Previous work has introduced a co-creation methodology for AI-enabled systems (Waschull & Emmanouilidis, 2022), supplemented by an evaluative approach for human-centricity assessment in such systems (Waschull & Emmanouilidis, 2023). This paper extends these works by introducing specific co-creation design patterns for human-AI decision-making processes, appropriately linked to the articulation of key decisions and decision-making process types, and the identification of their associated risks. Due to the complexity of the considered decision-making cases, the previously introduced methodology was substantially revamped so that co-creation activities are continuously applied throughout the project, instead of taking place at project milestone instances. To allow for such continuous co-creation processes, three different co-creation phases have been further introduced: an initial synchronous workshop (ISW), a virtual asynchronous refinement (VAR) and a final virtual synchronous workshop (VSW). Such phases can be relevant to every co-creation iteration, from the design all the way to final refinements, development, and testing. In addition to these contributions, the co-creation approach with extended design patterns offers a comprehensive approach to guide the design and development of AI-enabled systems in iterative cycles, thereby meeting the unique challenges of human-AI teaming in decision-making contexts. It extends earlier work on human-centric AI design processes (Waschull & Emmanouilidis, 2022) by observing specific needs that have arisen during co-creation for reusable design elements. From these needs, the following design patterns for decision-making were identified, providing actionable guidance to the co-design process:

P1. Use case introduction. This pattern is closely linked with the co-creation methodology and aims to establish shared understanding between co-creation collaborating partners. It includes the use case context and its objectives.

P2. User types are typically captured in use case diagrams in requirements elicitation. They are defined per use case. They include decision-makers or decision-making stakeholders.

P3. User stories. This is a standard requirements engineering pattern, useful for shared understanding.

P4. Components/functionality needed for user stories - also common in requirements engineering. The co-creation interest is in distinguishing between components deemed feasible, already available, and those out of scope or infeasible.

P5. Type of human-AI teaming (human-AI collaboration categories). This follows the typology introduced in section 2.

P6. Workflows for the ‘as is’ and envisioned ‘to be’ scenarios of the use case in an established format. They greatly help to establish a shared understanding of current and transformed processes with the human-AI typology. The business process modelling format (BPMN) is adopted for the co-creation.

P7. Decisions in the use cases relevant to the user stories. These are case-specific for human-AI decision-making.

P8. Success/evaluation criteria and KPIs (if relevant) per use case. These originate from best practices, standards, regulations, user requirements and verification/validation needs. They are domain and problem-specific.

P9. Risks refer to risks associated with the specific types of human-AI teaming in decision-making. In the context of AI decision-making, AI risk management is considered, such as defined in standards (e.g. NIST, ISO) and regulations (e.g. AI Act). Risks related to the workflows for the ‘as-is’ and ‘to-be’ cases need to be assessed.

These patterns are relevant to physical, virtual, synchronous and asynchronous activities at all phases. Different tools can be used to implement such patterns. In every phase of each iteration, these may include collaboration boards (physical flipcharts or virtual boards), workflow modelling tools, etc. A synthesis of co-creation outcomes from each iteration and phase facilitates the shared understanding among co-creators.

4. CO-CREATION IMPLEMENTATION AND RESULTS

The co-creation methodology is being implemented in the context of the HumAIne project (humaine-horizon.eu), which aims at delivering human-centric AI solutions for decision-making with human empowerment. The project involves Active Learning (AL), Neuro-Symbolic Learning (NSL), Swarm Learning (SL) and eXplainable Artificial Intelligence (XAI) applied in selected use cases within the domains of Smart Manufacturing (SM), Smart Cities (SC), Smart Healthcare (SH), Smart Finance (SF) and Smart Energy (SE). Co-creation activities are defined for different project stages: the definition and initial design, interim development, and final design refinements and development (Figure 1). Each phase includes ISW, VAR, and VSW phases, constituting a continuous co-creation process (Figure 2). The first phase spanned over three months and was carried out physically and virtually, using different tools (Table 1). All participants had access to virtual boards and a participant manual three weeks before VSW. Currently, the first co-creation phase is complete, and the interim phase is underway. Phase 1 started with pilot requirements, aided by a survey among participants to generate seeding information for ISW and produce user stories. Patterns P1 to P6 were applied, resulting in user stories (Figure 3), technical components and functionalities needed within the pilot, the mapping of success criteria, and human-AI synergies.

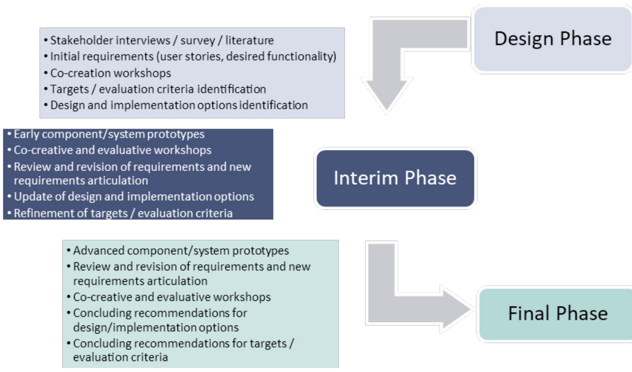


Figure 1. Co-creation phases

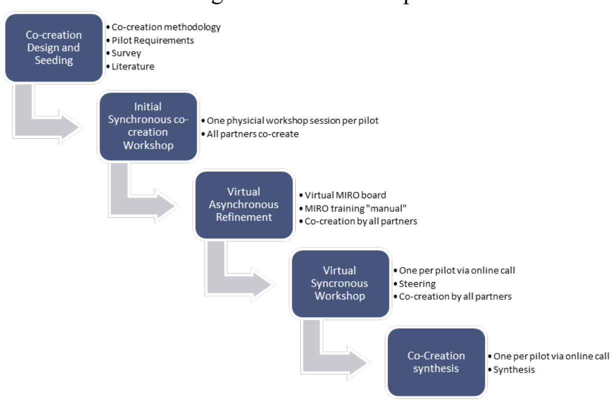
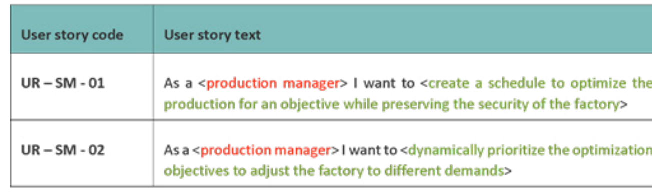


Figure 2. Co-creation steps at each phase

Table 1. Workshop details

Details and Tools	ISW	VAR	VSW
Date	April 2024	-	June 2024
Nº participants-mean	20	-	16
Physical	✓		
Virtual		✓	✓
Flipchart	✓		
MIRO[1] boards		✓	✓
Draw.io – BPMN	✓	✓	✓



User story code	User story text
UR – SM - 01	As a <production manager> I want to <create a schedule to optimize the production for an objective while preserving the security of the factory>
UR – SM - 02	As a <production manager> I want to <dynamically prioritize the optimization objectives to adjust the factory to different demands>

Figure 3. User story examples from the manufacturing use case

More details on reinforcement learning-based scheduling are provided in Hengel et al. (2024). The starting baseline for each targeted pilot process was captured as initial workflows of the 'as-is' situation. A shared view of the 'to-be' one expressed in user stories was not in place and only gradually emerged from the partners' co-creation activity. During VAR participants applied P7 to map key decisions to different decision-making process types for both the 'as-is' and 'to-be' processes. A view of the "to-be" workflow from the SM co-creation can be seen in **Error! Reference source not found.**, where the distinction between the development and the operational stages is discussed in section 5. This was among the outcomes of the ISW, with further processing after being transferred to MIRO boards, through the collaboration of partners in the virtual phases (i.e. VAR and VSW). The VSW step allowed further validation and updates, as well as initial risk mapping linked to key decisions of the process. The virtual co-creation space of the boards was appropriately structured for the co-creation, allowing asynchronous updates from participants and enabling them to go deeper into the individual elements of the co-creation patterns described earlier, including P8, setting a preliminary view of targets and potential evaluation criteria. The risk assessment in Table 2 illustrates an example of a risk-based approach for AI adoption, aimed to align with guidelines stated in standards and regulations, as mentioned earlier. It is noticeable that operational benefits expectations are modest at this stage. Usability should also be relevant to human factors. Customer trust is seen as having a high impact. Overall, AI risk assessment needs more work in further co-creation.

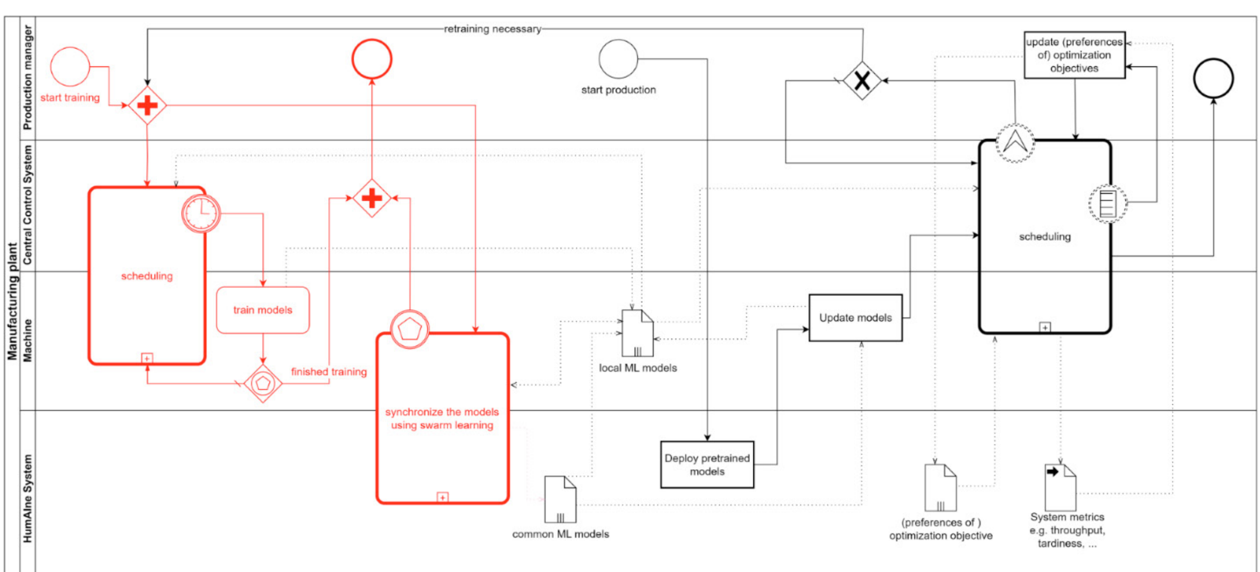


Figure 4. BPMN process workflows of "to be" situation after co-creation

[1] https://miro.com/

Table 2. Extract from Risk Assessment Matrix of the AI-enabled SM pilot

Risk ID	Failure Scenario	Harm to	Sub-category	Severity	Likelihood	Impact	Priority	Mitigation
17	Prolonged XR usage can make users feel sick.	Individuals	Physical Safety	9	7	63	1	Evaluate the consecutive time one can stay exposed to XR without becoming sick; add guardrails to prevent it
12	Accuracy reduction due to Data model aggregation in Swarm Learning	Organisation	Harm to the organisation's business operations	4	6	24	2	During development, the performance is validated in different experiments before deployment.
08	Low customer trust	Organisation	Organisation - reputation	3	7	21	3	Engage key customers in testing; advertise their perspective to lead others to buy into the AI solution

5. CO-CREATION EVALUATION AND DISCUSSION

In complex multi-stakeholder and multi-disciplinary decision-making, the involved stakeholders do not necessarily carry similar viewpoints, interests or information. The co-creation process was found to help stakeholders bridge existing knowledge gaps. Collaboration among diverse stakeholders would be challenging without a structured approach. The experience was that the use of common patterns P1-P9 made it easier to discuss decision challenges, establish a shared understanding of how the “to-be” process can be, as well as to appreciate associated risks and their impact in the context of the targeted domain. To gain an understanding of the added value of the co-creation methodology and the need for further improvements, the co-creation was evaluated at the end of the ISW and VSW steps. An evaluation survey was completed by representatives of the contributing partners. Suggestions made included points for further improvements, such as:

“*An explanation of the symbols used in diagrams is needed”*

“*The VSW step should be probably iterated*”

“*The Asynchronous phase was the weakest point as some technological paradigms were not understood to the point of being able to focus the contribution on user needs*”

How, why, and in which way humans and AI interact with one another were focal points in the collaborative activity for each use case. The “as-is” mapping was done by pilot partners for the representation of existing processes. The ‘to-be’ processes evolved through different phases of co-creation as technology developers and pilot representatives built a better vision of what could be accomplished and how it would change the existing processes. This dynamic and collaborative interaction during the first phase of co-creation resulted in the SM case having its “to be” process split into: the development stage and the operational stage (Figure 4). The former included aspects to be considered throughout the project development lifecycle. The stakeholder in charge of operationalising the process may have to factor in business-specific concerns at the time of deployment, and in doing so, the final operational process view may differ, for example, adjusting for AI risk management. The strong points, according to respondents, were:

“*The way the pilot work progressed via these workshops*”

“*The feeling that it was well thought out and planned*”

“*I really did enjoy the active engagement from all partners regarding the co-creation decisions and final results.*

“*MIRO boards and more interactive part*”

“*The focus on the user needs and case study comprehension from different perspectives*”

“*I enjoyed the switch between my contribution and subsequently working on the contribution of others, that was a great way to not fix on the same concept.*”

Table 4

Table 4. Evaluation of virtual co-creation steps (VAR and VSW)

Question	Score
Asynchronous Workshop Satisfaction rate	4.00
Synchronous Workshop Satisfaction rate	4.25
Engagement rate in the Asynchronous Workshop	3.88
Engagement rate in the Synchronous Workshop	4.42

Qualitative evaluations are more useful than quantitative analysis, due to the sample size (n=13). For completeness, a summary of evaluation results is seen in Table 3 and Table 4, with dissatisfaction/satisfaction marked by 1/5 on a Likert scale. Participants achieved a shared view of technologies, decisions and how to measure success. Results showed the importance of structured collaboration in complex, multi-stakeholder environments, strong engagement and satisfaction, and pointed towards improvements needed in the asynchronous part. The co-creation has now entered the second phase, and partners are refining co-creation entries, benefiting from continuing evaluation and experience from the process. As a result, they are in a better position to include in the co-creation process decision-making risks and the impact of AI on them.

6. CONCLUSION

While the contribution of co-creation and of human-centred design principles for delivering human-centric AI has been acknowledged in previous studies (Akhtar et al., 2024), human -AI teaming reshapes conventional thinking about systems aiding, augmenting, or replacing humans. Instead, AI actors are increasingly viewed as teammates, rather than just tools, and they require joint-consideration of human–AI teaming design optimisation (Xu & Gao, 2025) to overcome challenges of conventional co-creation approaches. The identification and reuse of design co-creation patterns for human-AI teaming is, therefore, a contribution to more effective co-design of human-centric AI solutions. The methodology effectively supports human-AI collaboration through a structured, agile framework for co-creation in dynamic decision-making contexts. The reusable patterns help to find solutions to common AI-human teaming challenges, including the identification of related risks. The effectiveness is demonstrated through multiple case studies, including a manufacturing context, highlighting their practical value and adaptability across diverse domains.

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