Co-Designing Team Design Patterns for Integration of New Technologies in USAR Operations

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ABSTRACT

Emerging technologies such as drones, wearables, robots, and AI offer clear potential for improving safety and situational awareness in Urban Search and Rescue (USAR), but their integration into practice remains difficult in multi-stakeholder projects. This Work-in-Progress paper presents an iterative co-design approach, structured by Socio-Cognitive Engineering (SCE), to derive Use Cases, Team Design Patterns (TDPs) and Interaction Design Patterns (IDPs) for USAR operations. Over multiple stakeholder sessions during field-test events, interviews, focus groups, observations, and evolving design artefacts were combined to elicit operational needs, role divisions, information requirements, and autonomy boundaries. These inputs were translated into representative use cases and an initial set of USAR-specific TDPs and IDPs. The current results should be seen as a stakeholder-informed baseline rather than field-validated design knowledge, but they already offer reusable guidance for coordination, information routing, and human–technology collaboration in high-risk operations.

Keywords

USAR, Team Design Patterns, Socio-Cognitive Engineering, HCI, Design thinking

INTRODUCTION

Large innovation projects in crisis response often struggle to keep technology development aligned with operational practice. In multi-stakeholder settings, partners can easily work in parallel on separate technical contributions, while questions about coordination, role division, information needs, and trust are addressed too late. As a result, technologies that perform well in isolation may still fit poorly into real work and add burden rather than support (Aschenbrenner et al., 2021).

This challenge is especially visible in Urban Search and Rescue (USAR), where squads operate under time pressure, uncertainty, and high risk. New technologies such as robots, sensors, and AI may offer added sensing or decision support, but their value depends on how well they fit into existing teamwork, communication, and decision-making. In this sense, USAR innovation is not only a technical problem, but a socio-technical integration problem (Kruijff et al., 2014; Murphy, 2004).

To address this, this paper combines Socio-Cognitive Engineering (SCE) with iterative co-design to derive Team Design Patterns (TDPs) and Interaction Design Patterns (IDPs) for human–technology collaboration in USAR (as part of the overall SYNERGISE project, Ziemian et al., 2026). SCE provides the structure for analysing work, roles, and use cases, while co-design activities help elicit and refine patterns grounded in practitioner input. The paper therefore focuses on two contributions: first, a co-design process for developing such patterns in a complex multi-stakeholder project; second, an initial set of TDPs and IDPs aimed at improving situational awareness and safety in USAR operations.

The main questions addressed are:

1. How can early co-design activities support SCE in specifying human- and mission-focused human–technology collaboration in large-scale innovation projects?
2. Which TDPs and IDPs emerge from these activities for integrating emerging technologies into USAR teamwork to improve first responders' situation awareness and safety?

RELATED WORK

Urban Search and Rescue (USAR) operations are best understood as a high-risk, multi-team ecosystem in which outcomes depend on coordination under uncertainty, not only on the technical performance of a single tool. When UAVs (Unmanned Aerial Vehicles) and wearables are introduced, their value depends on how they fit existing information flows and decision cycles: who interprets outputs, how uncertainty is communicated, when alerts trigger action, and how responsibility shifts when conditions degrade. Reviews of UAV-based situational awareness show that integration challenges are technical, organizational, and human-centered (MahmoudZadeh et al., 2024), while work on wearables highlights durability, battery life, non-intrusiveness, connectivity, and cross-agency interoperability constraints (Hegarty-Craver et al., 2024). Both technical and socio-technical factors therefore need early attention within the operational ecosystem.

European disaster-response robotics projects further show why this ecosystem perspective is necessary. NIFTi demonstrates that continuous end-user involvement, scenario-based development, and iterative field trials expose mismatches between laboratory assumptions and field realities, especially when the objective is improved situational awareness and coordination rather than stand-alone technical performance (Kruijff et al., 2014). TRADR extends this by emphasizing persistence over time: disaster response unfolds across repeated sorties and changing team compositions, requiring teams to preserve and reuse maps, observations, and interpreted findings across phases (Kruijff-Korbayová et al., 2015). These projects point to transferable principles for USAR ecosystem design: co-develop with practitioners, use operational scenarios and use cases as primary design objects, test early in realistic conditions, and support continuity of shared understanding. However, they do not provide a systematic way to package these insights into reusable, team-level design knowledge transferable across technologies and deployments.

Socio-Cognitive Engineering (SCE) offers a methodological basis for socio-technical integration because it starts from real work, cognition, and organizational constraints rather than technical opportunity alone (Sharples et al., 2002). Sharples et al. describe SCE as a human-centered methodology integrating task models, knowledge representations, user goals, and technical constraints through iterative movement between work analysis, specification, and evaluation (Sharples et al., 2002). This is relevant in USAR, where a system can meet technical requirements yet fail if it does not fit how people coordinate and decide (Sharples et al., 2002). Neerincx et al. show that SCE can work in complex settings by applying it to a long-term human–robot partnership, treating trust, cooperation, and adaptation over time as first-class design drivers (Neerincx et al., 2019). However, SCE remains generic: it is not tailored to high-risk, multi-team emergency operations, nor does it provide reusable, domain-specific team-level design artefacts that can be carried across projects (Sharples et al., 2002; Neerincx et al., 2019).

ISCRAM work on co-design with crisis professionals suggests that effective co-design in first-responder settings relies less on one formal method than on a practical toolkit of lightweight, field-compatible techniques. Participatory design and emergency-management co-creation studies use future workshops, low-fidelity prototyping with paper materials such as PICTIVE, whiteboards and Post-its, scenario walkthroughs and disaster re-enactments, video prototyping, brainstorming, interactive mind-mapping, guided interviews, focus groups, contextual inquiry, observation, and affinity diagramming (Hughes, 2014; Petersen et al., 2015; Radianti et al., 2018; Elmasllari, 2019). Rather than high-fidelity prototypes, these studies use low-threshold artefacts that let practitioners react quickly, critique assumptions, and connect technologies to concrete operational moments (Hughes, 2014; Petersen et al., 2015). This matters in crisis settings, where participants have limited time, diverse roles, and strong sensitivity to realism, feasibility, and accountability (Elmasllari, 2019).

A notable pattern is that these tools are rarely used in isolation. Scenario-based activities help participants imagine how technologies fit actual mission rhythms (Petersen et al., 2015; Radianti et al., 2018), while sketches, maps, and interface mock-ups make abstract design choices discussable in terms of workload, information routing, escalation, and trust (Hughes, 2014; Radianti et al., 2018). Interviews and focus groups capture role differences, and observations or contextual inquiry compare stated preferences with actual practice (Elmasllari, 2019). Recent work also shows the value of structured workshop elicitation around collaboration barriers and needs, supported by evolving artefacts rather than polished systems (Steen-Tveit et al., 2023).

Building on this work, our article addresses the gap between methods that analyze and design socio-technical systems (SCE) and pattern-based approaches that describe effective human–agent teamwork (TDPs). We apply SCE to a USAR ecosystem context in the project's early steps, when information is collected but results are not yet field-tested, to elicit foundational work insights and derive and refine representative use cases with stakeholders. From these inputs, we develop an initial set of USAR-specific Team Design Patterns and validate them with practitioners, making the results reusable team-level guidance for integrating multiple technologies into USAR workflows rather than one-off recommendations.

METHODOLOGY

An initial stakeholder meet-up and four multi-day field-test events involved first responders, squad leaders, medical staff, drone operators, and technical support personnel. This provided access to multiple roles in realistic mission conditions and grounded feedback in observed system behaviour, including degraded conditions such as unstable connectivity and incomplete sensor outputs.

Data collection combined structured interviews, guided individual interviews, focus groups, field observations, and short intercept questions during hands-on trials. Notes and transcripts were produced during or after sessions. Between events, findings were coded into operational needs and constraints, role-specific information needs, acceptable human–automation allocations, and trust conditions such as transparency and confidence communication. These were translated into candidate TDPs and IDPs and iteratively refined.

Co-design activities

At the first stakeholder meet-up, structured interviews with 8 technical stakeholders and 2 end-user representatives captured technology capabilities, integration constraints, and expected operational roles. Early TDP examples and storyboards were used as prompts.

During field tests, short guided interviews with 12 participants from roles including base operations, squad leader, medical expert, and field responder focused on role-based information needs using HMI sketches and example visualizations.

Two focus-group sessions with 10 participants each discussed a draft concept of operations and initial SCE use cases, supported by Mentimeter polling. In a later field test, two additional stepwise use-case discussions were held with 8 participants each, plus one breakout session with 2 experts. These sessions focused on ecosystem coherence, acceptable automation, role division, and escalation logic.

Field observations were conducted throughout the test modules to compare stated preferences with enacted work. In the final field test, 6 participants were asked short questions during or immediately after hands-on trials to capture reflections on workload, situation awareness, and usefulness.

Design artefacts

Design artefacts structured and updated the analysis: a concept of operations, role descriptions, storyboards, low-fidelity HMI sketches, and SCE use cases with claims. These artefacts aligned operational and technical perspectives, made design assumptions explicit, and supported discussion of workload, information routing, control allocation, and expected operational effects. TDPs and IDPs served as final consolidation artefacts, capturing recurring coordination and interaction solutions.

Design process

The process followed a repeated cycle: collect input, update artefacts, analyse findings, revise candidate TDPs and IDPs, and bring these back into the next event. SCE provided the analytical structure, while co-design activities supplied practitioner input to iteratively develop the patterns. The figure below visualizes the design process. Interview types are linked to project meetups and test moments, while design artefacts are plotted on the same timeline. Creation is shown in boxes, and arrows indicate when artefacts were iterated until crystallizing into final forms.

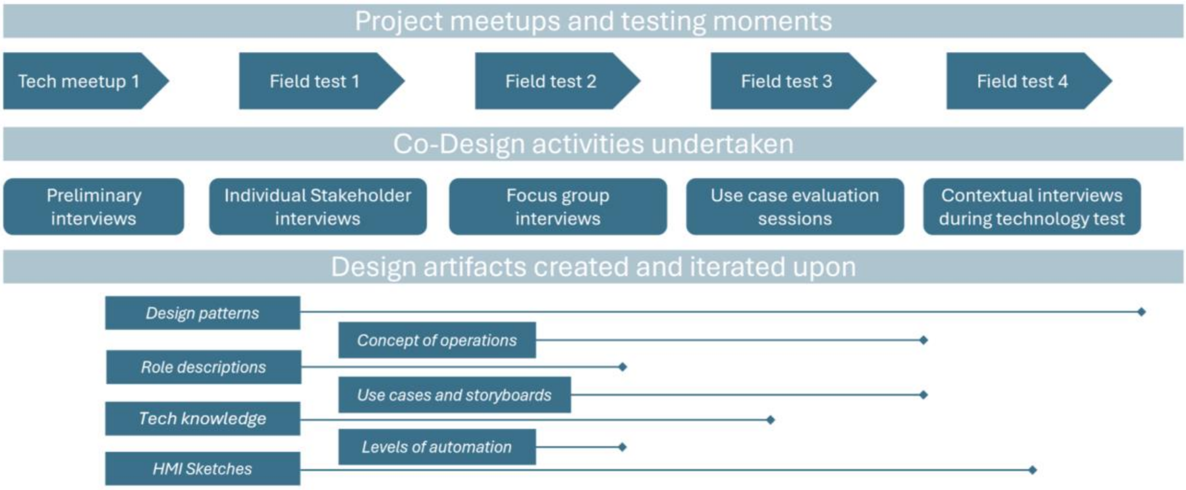


Figure 1: Design process covering approximately one year of our project

RESULTS

The results are presented as (a) four representative USAR use cases and (b) a set of Team Design Patterns (TDPs) and Interaction Design Patterns (IDPs) that capture recurring solutions for integrating robotics, sensors, and AI into operational workflows. The use cases translate the qualitative insights from field tests and co-creation sessions into concrete, scenario-driven descriptions of work in context. Each use case is documented in a structured table that specifies the operational intent, involved actors and roles, pre- and post-conditions, technology requirements, a step-wise action sequence, and a set of explicit claims about expected effects on safety, situation awareness, workload, and mission performance.

Use Cases

UC1

Health and environmental monitoring was identified as a core use case due to recurring concerns about unnoticed overexertion, heat stress, and hazardous exposure during operations. Responders emphasized that physical strain often escalates without clear indicators, while frontline personnel cannot actively monitor detailed data during missions.

This use case therefore focuses on continuous sensing combined with role-based escalation, enabling early intervention and improved responder safety without increasing workload.

	UC1 Health and Environmental Monitoring
Visual	
TDPs:	TDP3, TDP6, TDP7
IDPs:	IDP2, IDP4
Actors:	First responder, Squad Leader, Medic, Safety Officer
Pre-Condition:	Wearables active and connected before entry.
Post-Condition:	Health alerts handled; intervention performed if needed.
Technology requirements:	Physiological wearables, health sensors and gas exposure sensing, connectivity, real-time alerts, role-based dashboards, data logging
Action Sequence:	1. **Equipment Check & Deployment** First responder put on sensors; safety officer confirms connectivity.

	2. Live Monitoring Vitals tracked during suppression; warnings issued if thresholds exceeded. **3. Remote Oversight** Safety officer monitors dashboard; alerts sent to squad leader. **4. Intervention** First responder extracted if condition worsens; medic logs health data. **5. Post-Incident Reporting** System logs exported; data used for review.
Claims:	**CL1:** Decreased physical workload via early warnings. **CL2:** Improved safety through gas exposure monitoring. **CL3:** Safety improved via remote escalation. **CL4:** Workload reduction through safety officer oversight. **CL5:** Better medical decision-making using vitals history. **CL6:** Improved SA on personnel status for command. **CL7:** Supports continuous learning through health data review. **CL8:** Improves mission performance through better personnel management.

Figure 2: Health and environmental monitoring use case

UC2

This use case reflect the need for rapid, shared situational awareness at the incident level. Participants highlighted that early decisions on sectorization and resource allocation are often made with incomplete information. As a drone pilot, who in daily life works as a drone operator for a fire brigade, stated during the second field test: "*Using drones for wide area assessment and sectorization is not a future idea – we already do this at our fire department*". While such practices are established within some fire brigades, employing drones for wide area assessment is relatively new for Urban Search and Rescue (USAR) operations and is not yet a standard procedure in that domain.

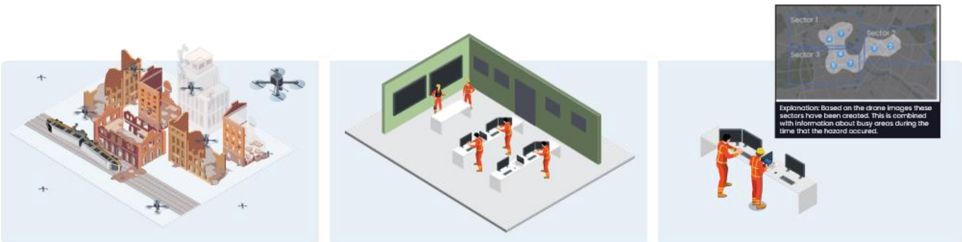
	UC2 Wide Area Assessment
Visual	
TDPs:	TDP1, TDP4, TDP6
IDPs:	IDP1, IDP3
Actors:	Drone Operator, Frist responders, Command Center Staff, Analyst
Technology requirements:	Aerial drone, high-resolution video, GPS/geotagging, live command feed, visual annotation
Pre-Condition:	Drone operational and connected; need for aerial view identified.
Post-Condition:	Hazards assessed; situational awareness increased.
Action Sequence:	**1. Deployment** Launch drone; share feed with command. **2. Area Assessment** Perform wide pass and identify hazards. **3. Close-Up Inspection** Zoom on specific locations for confirmation. **4. Data Sharing** Annotate and distribute visuals; drone remains in overwatch
Claims:	**CL1:** Improves SA on environment for squads. **CL2:** Enables safer squads movement planning. **CL3:** Increases planning speed and decision tempo. **CL4:** Lowers workload by replacing physical reconnaissance. **CL5:** Improves shared SA between field and base.

Figure 3: Wide area assessment use case

UC3

This UC emerged as a response to the tension between acting quickly and avoiding early human exposure in unstable structures. Across co-creation sessions, drones were consistently described as a way to gain actionable insight before committing squads, as a first responder commented: "*If the drone already shows a sector is empty, we don't need to send people in. That saves time – and it reduces risk.*"

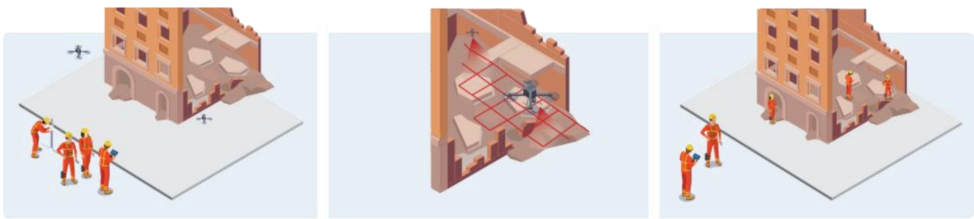
	UC3 Indoor Drone Exploration and Victim Detection
Visual	
TDPs:	TDP1, TDP2, TDP4, TDP5
IDPs:	IDP1
Actors:	Drone Operator, Analyst, Squad Leader
Pre-Condition:	Structure unsafe for entry; drone available.
Post-Condition:	Victim locations marked on C3I map; team briefed.
Technology requirements:	Indoor drone, visual/thermal camera, live video link, autonomous exploration, shared map export
Action Sequence:	**1. Deployment & Startup** Drone setup and connection to C3I. **2. Autonomous Navigation** Drone maps victims, hazards, and structural features. **3. Live Monitoring** Analyst verifies detections, tags hazards. **4. Coordination** Analyst shares map; Squad leader updates plan.
Claims:	**CL1:** Video stream improves pre-entry SA (measured with SAGAT). **CL2:** Map improves pre-entry SA (C3I mapping, LiDAR). **CL3:** Improves responder safety through hazard mapping. **CL4:** Autonomous detection increases speed and robustness of victim localization. **CL5:** Analyst involvement improves trust calibration. **CL6:** Adaptive autonomy maintains acceptable operator workload.

Figure 4: Indoor drone exploration and victim detection use case

UC4

This UC is for situations where environments are inaccessible, confined, or too hazardous for humans or aerial platforms. Responders repeatedly emphasized the value of substituting human entry with robotic inspection, as it is a good way to reduce human exposure to unstable structures.

	Use Case 4 Detailed Indoor Exploration with Robots
Visual	
TDPs:	TDP2, TDP5, TDP7
IDPs:	IDP1, IDP3
Actors:	Robot Operator, Squad Leader, First responders
Pre-Condition:	Structure contains inaccessible zones; robot operational.
Post-Condition:	Hazards marked; victims located; squad proceeds safely.
Technology requirements:	Ground robot mobility, teleoperation and autonomy, RGB/thermal cameras, local mapping, confined-space inspection tool, robust communications
Action Sequence:	**1. Deployment** Robot checks and calibration. **2. Navigation** ANYMAL explores autonomously or manually. **3. Detailed Inspection** SNAKE arm used for small spaces. **4. Situation Update** Findings reported; robot retrieved or repositioned.
Claims:	**CL1:** Improves responder safety by sending robot into danger zones. **CL2:** Improves SA through camera inspection.

	CL3: Increases victim detection rate. **CL4:** Identifies hazards for safer routing. **CL5:** Builds trust through operator-validated visuals. **CL6:** Improves operational speed.

Figure 5: Detailed indoor exploration with robots use case

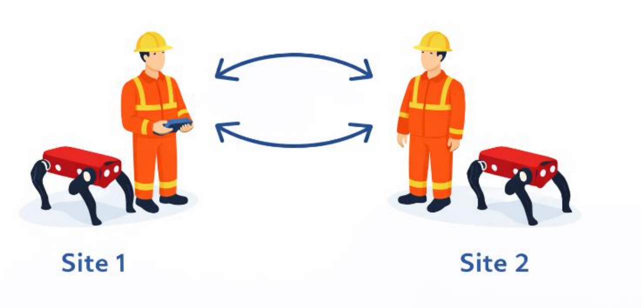
Team Design Patterns

The Team Design Patterns (TDPs) below emerged from recurring coordination and organizational challenges observed during interviews and field tests. Participants repeatedly noted that while robotic and AI technologies are advancing quickly, squad structures and role definitions often do not adapt at the same pace, creating friction during operations. As one responder stated: "*We're still operating with our old organization, and the new systems don't fit inside that.*" This motivated TDPs that address role allocation, authority, and coordination across operational levels, not just interface design.

A strong theme was the need to separate cognitively demanding roles. Responders emphasized that piloting, sensor interpretation, and tactical decision-making cannot safely be combined, which informed patterns such as splitting robot control and analysis roles and dynamically assigning operators based on workload and phase. Participants also stressed that human authority must remain central in safety-critical decisions. As one Squad leader noted: "*It should propose something and I will decide*." The TDPs therefore define clear task boundaries between humans and machines, emphasizing AI-supported suggestions, human approval for consequential actions, and structured handovers rather than automated command decisions.

TDP1

This first TDP emerged from the need to maintain situation awareness both locally at worksites and centrally at the Base of Operations (BoO) during drone-supported exploration. Responders found that fixed operator placement created bottlenecks when demands shifted across sectors. By assigning operators to sectors while allowing deliberate redeployment as phases or workload change, squads can better match operator attention to real-time operational needs, ensuring both flexibility and sustained expertise at critical points. More broadly, this pattern can be generalized: place human expertise where coordination pressure is highest, while preserving continuity in tool ownership, handover, and interpretation. This makes the pattern relevant beyond drones, for any distributed system in which sensing, control, and analysis need to shift with operational tempo.

	TDP1 Dynamic Robot Operator Deployment by Sector & Worksite
Visual	
Description	Assign operators to **sectors/worksites**; operators can **embed in squads** for local SA or work from the **BoO** for cross-sector SA. Swap operators deliberately as phases/load change to where the robots are needed. Keep robots with the same operators, and operators and analysts in the same squad.
Intent	Balance workload for robot operators, make SA available at BoO and in squads.
Context	Multiple robot human squads supporting several worksites/sectors; squads on the ground; BoO managing overall ops.
Problem	Fixed operator locations cause bottlenecks and confusion; local squads and the BoO need different SA.
Solution	• Bind each robot to a **sector/worksite** with **an operator and an analyst.** • Two postures: **Embedded** (with squad) vs. **BoO-based** (orchestrating multiple robots). • Handover triggers: phase change, surge demand, comms shift, start/end of worksite ops.

Roles	Drone operator and analyst; Squad Lead; Sector Lead; BoO Operator and lead;
Taks balance (Human vs Machine)	**Human:** sector assignment, control authority, prioritization, cross-sector coordination, final route/entry decisions. **Machine:** stabilization, navigation assist, perception/mapping, alerting with confidence, health/telemetry.
Consequence	Local SA when needed; broader SA when helpful; resilience via explicit swaps; requires UI support.
Related TDPs/IDPs	TDP4, TDP5, TDP6; IDP1, IDP2.

Figure 6: Dynamic robot operator deployment by sector and worksite

TDP2

This second TDP addresses the recurring problem of human exposure in unknown or hazardous environments. Across co-creation sessions, responders emphasized the value of robotic reconnaissance before human entry to reduce risk while maintaining tempo. The pattern formalizes phased entry: robots explore first, identify hazards, and suggest routes, after which humans enter through explicit go/no-go gates.

Broader, this pattern can be generalized as remote-first risk reduction principle: use lower-risk assets to reduce uncertainty before committing people. That principle is transferable to other technologies and domains wherever unsafe environments, incomplete information, and time pressure must be balanced.

	TDP2 Robots First, Then Humans Protocol
Visual	
Description	Robots explore first; humans enter only after safe passage is guaranteed. Robots and humans are working in an alternating fashion sweeping areas or floors for speed.
Intent	Reduce human exposure while maintaining tempo.
Context	Unknown or unsafe areas under time pressure.
Problem	Early entry increases risk; waiting blindly wastes time.
Solution	• **Phase A: Robotic Recon** (autonomous/assisted) to map, detect hazards, propose ingress. • **Go/No-Go markings** (e.g., coverage ≥ X%, hazards, ≥ Z viable routes). • **Phase B: Human Entry** after a standardized Recon Brief; keep robotic overwatch.
Roles	Robot operator and analyst; Squad lead; First responders.
Taks balance (Human vs Machine)	**Human:** set objectives, interpret brief, decide go/no-go, choose route, manage risk. **Machine:** run coverage sweeps, detect/label hazards, provide confidence
Consequence	Lower exposure; clearer entry rationale; risk of delay if robots struggle.
Related TDPs/IDPs	TDP5, TDP6; IDP2.

Figure 7: Robots first, then humans protocol

TDP3

This next TDP was developed to use AI support without weakening human accountability. Participants repeatedly warned that over-reliance on automated outputs could introduce new risks in high-consequence situations. This pattern therefore frames AI outputs as suggestions, supported by confidence indicators and rationale, while keeping final authority with human decision-makers.

Generalized, this becomes a principle of advisory automation with human authorization**:** automation may accelerate interpretation and option generation, but consequential decisions remain explicitly human-owned. This makes the pattern usable well beyond AI agents in USAR, for any support system that influences decisions under uncertainty.

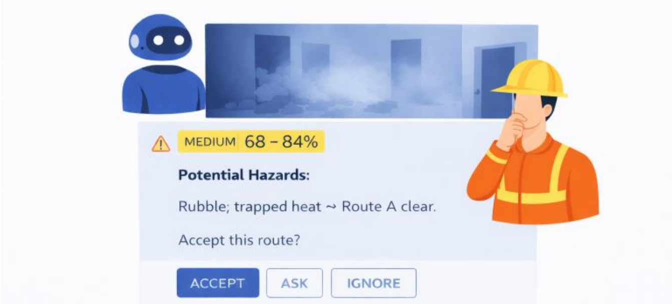
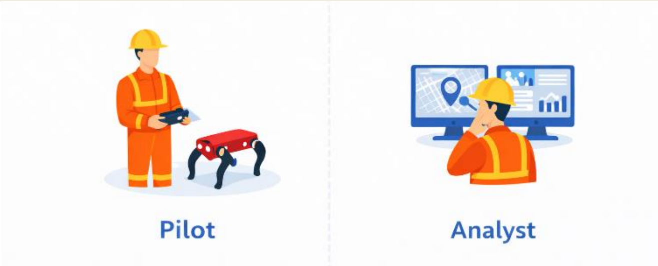
	TDP 3 AI Agents for Suggestions, Not Decisions
Visual	
Description	AI proposes actions based on sources; humans decide with rigor scaled to consequence. This can be both for sending information or alerts to other actors or for taking other actions.
Intent	Use AI speed without losing accountability.
Context	AI proposes routes, classifications, triage, next actions.
Problem	Over-automation endangers; under-use wastes capability.
Solution	• Prompt alerts with suggestion for course of action. • Show **suggestion cards** with rationale and **confidence** (IDP2); include alternatives. or ignore options. • Human confirmation required for safety, log decisions.
Roles	AI Agent; Operator/Analyst (reviewer); Squad lead (approver for consequential).
Taks balance (Human vs Machine)	**Human:** evaluate/accept/modify/reject; authorize consequential actions; document rationale. **Machine:** generate suggestions; compute confidence; surface evidence; execute only upon approval.
Consequence	Calibrated trust; auditability; slight added latency.
Related TDPs/IDPs	TDP6; IDP2

Figure 8: AI agents for suggestions, not decisions

TDP4

The following TDP emerged from the observation that a single operator could not safely control a robot while also interpreting incoming sensor data. Separating the pilot from the analyst reduces cognitive load, improves interpretation quality, and supports clearer communication with leadership.

This pattern can be generalized as separating control from interpretation when both demand sustained attention. It is therefore relevant not only for robot operations, but for any setting where one person would otherwise be overloaded by having to steer a system and simultaneously make sense of complex outputs.

	TDP4 Split Role for Robot Control and Data Analysis
Visual	
Description	Separate **Pilot** (control) and **Analyst** (sensing) to reduce overload and improve detection. Every squad that has a pilot for a drone or a robot also needs an analyst that can deal with the information and communicate it to the right stakeholders.
Intent	Improve safety and sensor interpretation quality.
Context	Tight maneuvering; many sensors and datapoints; limited bandwidth.

Problem	One person can't fly precisely and – at the same time- interpret everything while staying safe in a worksite environment.
Solution	• **Pilot:** vehicle state, collision safety, framing on request. • **Analyst:** interpretation, communication • **Squad leader or BoO dispatcher:** communication, decision making.
Roles	Robot operator and analyst; Squad lead
Taks balance (Human vs Machine)	**Human (Operator/Analyst):** manual operating; analytic judgements; confirmations; task prioritization. **Machine:** stabilization, obstacle warnings, SLAM/map updates, detection proposals with confidence.
Consequence	Better flight safety and detection; requires two people and disciplined comms.
Related TDPs/IDPs	TDP1; IDP1.

Figure 9: Split role for robot control and data analysis

TDP5

The last TDP was identified to balance speed and safety. Responders noted that autonomy can save time during broad exploration, but becomes risky in precision tasks or near personnel. This pattern therefore uses autonomous operation when conditions permit, while requiring manual control when work becomes detailed, safety-critical, or closely coupled to human activity.

As a broader principle, it can be generalized as adaptive autonomy by context**:** shift between automated and manual control depending on proximity, risk, and task precision.

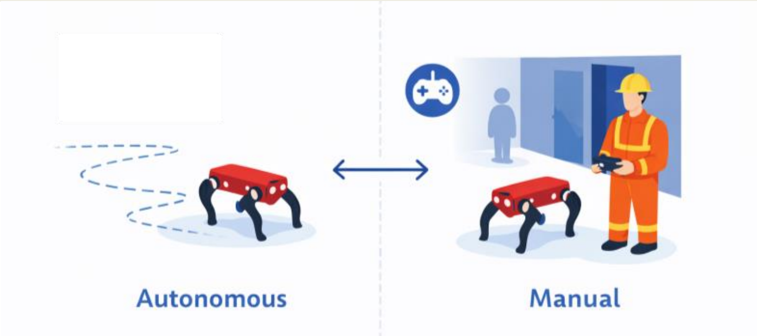
	TDP5 Autonomous Exploration, Manual when required
Visual	
Description	When doing precision steering or working near people at the worksite; manual control is mandatory. When unaccompanied; autonomous exploration allows to save time and making it possible to do simultaneous work. This shifts the focus between safety and speed when needed.
Intent	Optimizing time use while taking caution when needed.
Context	Robots moving between sectors and operating at worksites.
Problem	Autonomy is efficient but risky around people; manual is safer for the robot itself and the humans around it but slower overall.
Solution	• Robots can be sent into floors or areas and explore autonomously. • When needed for precise tasks or working close to humans, manual operation mode is used.
Roles	Robot operator and analyst; Squad lead
Taks balance (Human vs Machine)	**Human:** manual operating; task execution at worksite; risk management; accept/reject AI suggestions. **Machine:** autonomous transit/exploration when alone; path planning; hazard/target proposals; proximity/uncertainty cues; safe-stop/hold.
Consequence	Safer near humans; faster coverage when alone; requires reliable proximity sensing and clear UI.
Related TDPs/IDPs	TDP2, TDP1; IDP1, IDP2.

Figure 10: Autonomous exploration, manual when required

Interaction Design Patterns

The Interaction Design Patterns (IDPs) focus on how information generated by robots, sensors, and AI systems should be communicated to different roles. Across interviews and during field tests, participants repeatedly warned that undifferentiated or overly detailed information can overwhelm users and obscure critical signals, particularly in dynamic field conditions.

Responders emphasized that different roles require fundamentally different representations of the same underlying data. This was clearly expressed during co-creation sessions: “*Raw medical data should only be visible to medics.”* and *“Squad leaders need to see alarms only”.* On the other hand, trust in AI-generated information emerged as another central theme: “*If the system tells me stress is rising, I need to know why. Without understanding where that prediction comes from, I would not trust the advice.*”. Together, these insights shaped IDPs. Rather than maximizing information availability, the patterns prioritize timely, interpretable, and trustworthy interaction, supporting calibrated trust and effective decision-making across operational phases and organizational levels.

IDP1

This first IDP was created to address information overload in multi-role, multi-phase operations. Responders repeatedly noted that receiving too much data can bury critical cues. This pattern ensures that each actor sees only the information relevant to their role and current phase, while still allowing progressive disclosure or emergency override when needed. In generalized form, this becomes a principle of selective information routing**:** distribute information according to role, task, and urgency rather than exposing all data equally to all users.

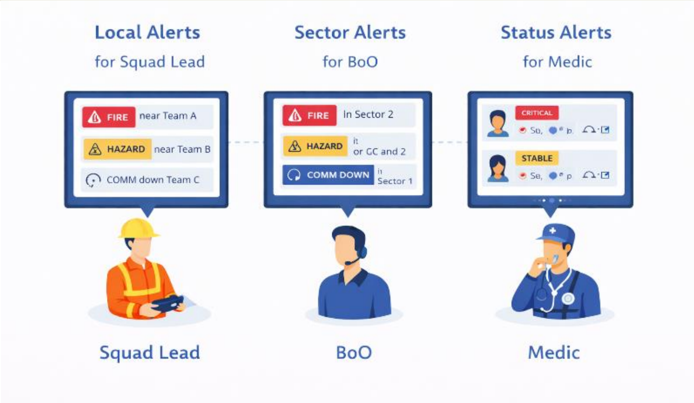
	IDP1 Role-Based, Context-Specific Information Distribution
Visual	
Description	Route the right info to the right person at the right time; hide the rest by default. Focusing on local squad information for squad leads, sector related alerts for BoO and detailed medical status information for the medical staff. Every role should get the information presented so that they can act upon it within the tasks of their role. The **squad leader** should have status indicators that are simple and readable, because they do not have the time to look into details. The **BoO** should have an overview of all squads, with alerts when there are a lot of status changes at once. **Medical personnel** should have detailed information about e.g.: heart rate, blood oxygen levels, and other relevant health related information. This same buildup holds for location, comms status and environmental sensor status information.
Intent	Minimize distraction and missed signals with role- and phase-aware routing.
Context	Multi-role squads; shifting phases; heterogeneous devices.
Problem	Undifferentiated feeds overload users and bury critical cues.
Solution	• **Role Profiles** (Sector and Squad Lead, BoO) with default information presentation and alert levels. • **Progressive disclosure**; “break-glass” broadcast for emergencies. • **Targeted alerts** based on role like field medics but also doctors at BoO
UI/Modalities	Role dashboards
Related TDPs/IDPs	TDP1, TDP5.

Figure 11: Role-based, context-specific information distribution

IDP2

This second IDP emerged from the need to calibrate human trust in AI outputs. During exercises, responders expressed concern about both misleading certainty and hidden uncertainty. This pattern therefore makes uncertainty explicit through confidence bands, rationale, and alternative options, helping users judge whether and how to act on AI support. More broadly, it can be generalized as a principle of transparent uncertainty communication**:** decision support should reveal not only what a system suggests, but how sure it is, why, and under what conditions it may fail.

<table>
<tr><th></th><th>IDP2 Confidence Score for AI Agent Suggestions</th></tr>
<tr><td>Visual</td><td>
</td></tr>
<tr><td>Description</td><td>Expose uncertainty clearly to calibrate human trust in AI outputs. Both using a certainty percentage and an explanation with words that can be checked if the user wishes to. Users will slowly learn to get a feeling for percentages, but additional explanation is needed.</td></tr>
<tr><td>Intent</td><td>Prevent over- and under-trust.</td></tr>
<tr><td>Context</td><td>AI proposes classifications, routes, hazards, triage.</td></tr>
<tr><td>Problem</td><td>Single numbers imply false precision; hidden uncertainty misleads.</td></tr>
<tr><td>Solution</td><td>Show an Explanation, a confidence band (Low/Med/High) + numeric interval; provide rationale/evidence and failure cues (OOD, sensor health).
Offer alternatives with relative confidence and quick actions (accept, request evidence, suppress).
Possible: Provide calibration hints (“High on similar past scenes; sensor X degraded”).</td></tr>
<tr><td>UI/Modalities</td><td>Badges with brief rationale; expandable evidence section; consistent icons.</td></tr>
<tr><td>Related TDPs/IDPs</td><td>TDP2, TDP3, TDP6.</td></tr>
</table>

Figure 12: Confidence score for AI agent suggestions

DISCUSSION

In the study a number of TDPs and IDPs have been explored and validated for the USAR setting. The current set serves as a validated baseline, not a complete library; more TDPs and many IDPs may still emerge as systems evolve. While some patterns may seem generic at higher abstraction levels, their true value lies in providing a consistent foundation that, when applied across organizations and partners, streamlines integration and minimizes socio-technical friction. However, if TDPs are to be reusable, maintenance and governance of these patterns become central: versioning, translating patterns across domains, and aligning different abstraction levels (too high becomes vague; too low becomes brittle).

Many of the current patterns are conservative in their use of autonomy, reflecting current technical and organizational readiness; increased autonomy is plausible later, but only when trust calibration, transparency, and accountability mechanisms are sufficiently mature.

With respect to the study, the limited number of contact opportunities made it difficult to consistently maintain a comprehensive overview, given that USAR spans multiple roles, phases, and organizational levels. It is also important to note that participant numbers per role were limited during the co-design activities, affecting representativeness. Most participants were already embedded in the project ecosystem, which may also have influenced their perspectives. Even so, artifacts such as the concept of operations and use cases helped structure discussions and turn stakeholder input into candidate patterns.

CONCLUSION

This paper presented an iterative co-design approach for deriving Team Design Patterns (TDPs) and Interaction Design Patterns (IDPs) for integrating emerging technologies into USAR operations, alongside preliminary patterns. A consistent theme is reducing uncertainty and improving safety while preserving shared situation awareness, clearly defined team roles, role-based information needs, and human accountability for decisions. This provides a structured foundation for development of human-machine teaming patterns in complex, dynamic, and safety-critical environments.

While the paper combines the Socio-Cognitive Engineering (SCE) method, co-design activities, and pattern formulation in a way that proved useful in practice, the current presentation does not yet make the process sufficiently transparent or reproducible for other researchers. This should be described more robustly in future work. The resulting patterns should therefore be understood as an analytically grounded, stakeholder-informed baseline, not yet as field-validated design knowledge. Although they were refined through interviews, focus groups, walkthroughs, and observations, they have not yet been tested in a dedicated integration test with mature, interconnected systems. Future work should focus on validating the patterns under operational conditions and providing a more explicit, systematic description of the methodology to ensure both patterns and approach are reusable.

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