Deliverable N. 5.2, 2nd release

Case studies and results of validation studies

Authors:

DFKI, ENAC (UC1), Thales, Embraer (UC2), LiU (UC3), Skyway, DBL (UC4), ECTL, Suite5, ENG (UC5), CERTH (UC6)

Abstract:

This deliverable presents the outcomes of Task 5.2 “Communication models for XAI in Human-AI Teaming” and the preliminary results of Task 5.3 “Validation of XAI Strategies and Communication Models”, capturing the progress of the use cases by month 36 (August 2025).

Information Table

Deliverable Number	5.2
Deliverable Title	Case studies and results of validation studies
Version	2.0
Status	Final
Responsible Partner	DFKI
Contributors	ENAC, THALES, Embraer, Bordeaux INP, CATIE, LFV, LiU, Skyway, DBL, Suite5, ECTL, ENG
Contractual Date of Delivery	31.08.2025
Actual Date of Delivery	27.08.2025
Dissemination Level	Public

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Document History

Version	Date	Status	Author	Description
1.1	05.11.2024	Repository Template & Deliverable Outline	DBL & DFKI	Template for all partners
1.2	Jan-May, 2025	Draft contribution in the repository	UC Leaders, DBL	UC contributions in the Repository with iterative reviews to ensure consistency
1.3	26.06.2025	First Draft	N. Minaskan (DFKI)	1st draft of the document created by using all the UC contributions
1.4	07.07.2025	First Draft	R. Venditti (DBL)	First review with suggestions about improving main body + write up of conclusion
1.5	31.07.2025	Second Draft	N. Minaskan (DFKI)	Integration of comments
1.6	07.08.2025	Third Draft	R. Venditti (DBL)	Final review and quality check
2.0	26.08.2025	Final Version	N. Minaskan (DFKI) R. Venditti (DBL)	Final version for submission

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

List of Acronyms

Acronym	**Definition**
AAM	Advanced Air Mobility
AOCC	Airport Operation Control Centre
ASW	Airport Safety Watch
ATCO	Air Traffic Controller Officer
ATIS	Automatic Terminal Information Service
CISP	Common Information Service Provider
CLT	Construal Level Theory
CTOT	Calculated Take-Off Time
DUC	Digital UTM Coordinator
ECAM	Electronic centralised aircraft monitor
ECG	Electrocardiogram
EFB	Electronic Flight Bag
EMG	Electromyography
EOBT	Estimated Off-Block Time
EPOG	Eye Point of Gaze
ETA	Estimated Time of Arrival
GSR	Galvanic Skin Response
HAT	Human AI Teaming
IA	Intelligent Assistant

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

ISA	Intelligent Sequence Assistant
KPI	Key Performance Indicator
LLA	London Luton Airport
ND	Navigation display
NLP	Natural Language Processing
PFD	Primary Flight Display
PPG	Photoplethysmogram
SECI	Socialisation, Externalisation, Combination and Internalisation (model)
SHAP	SHapley Additive exPlanations
STPA	Systems Theoretic Process Analysis
SWIM	System-Wide Information Management
UC	Use Case
XAI	eXplainable AI

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Table of contents

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Executive Summary

This document describes the XAI strategies and communication models designed in the six HAIKU use cases, capturing their status at month 36 (August 2025).
Following the work documented in D5.1, the Construal Level Theory (CLT) is used as the XAI framework for designing explainability in the HAIKU Use Cases (UCs). Overall, following VAL2 activities, all six use cases validated the communication models and derived high-level results and conclusions on XAI.
It is possible to conclude that the CLT framework is a valuable approach for designing XAI strategies and structuring robust communication models. By enabling flexible, layered explanations that adapt to evolving operational needs and user contexts, the framework helps build trust, transparency, and informed decision-making in human–AI collaboration.

The CLT framework proved especially effective in use cases where there was:

- A well-defined Concept of Operations (ConOps);
- Clear Human-Machine Interface (HMI) requirements;
- Enough decision-making time for users to process layered explanations;
- Opportunities to support context-specific queries and gradual information disclosure.

These conditions were met in UC2, UC4, and UC6, where the framework helped tailor information flow and manage feedback loops effectively.

However, the project also highlighted limitations. The CLT framework was less effective in contexts requiring split-second decisions (UC1), in scenarios with very long or unconstrained timeframes (UC5), or when the concept was still too abstract (UC3) - although in the case of UC3, it did contribute to defining the XAI elements of the ConOps.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Introduction

The previously released D5.1 (*Strategies in XAI* (HAIKU, 2023)) reviewed the theory, models, and methods available to explore Explainable AI (XAI). In particular, D5.1 introduced Construal Level Theory (CLT) ([1,2]). CLT assumes that humans' mental (construal) representations are influenced by factors such as:

- Temporal distance (how far into the future an event is perceived);
- Spatial distance (how physically close or distant an object or event is perceived);
- Social distance (how emotionally close or distant a person or group is perceived), and
- Hypotheticality (how likely or certain an event is perceived to occur).

CLT was selected as the XAI framework for exploring explainability in the HAIKU Use Cases (UCs). As shown in Table 1, CLT defines six levels of abstraction. The six involve progressively more information, explanatory content, user information needs, and consumption time. A fuller description of the CLT framework and levels can be found in [2].

Level of abstraction	**Type of information/construal**	**Content/measurement model**	**User information needs and consumption time**
CLT 1	Executive summary/main claim	This key outcome was/will be achieved as shown by these key indicators	Provide further definition of entities in the plan; provides success or failure indicators of the plan/ ~10s
CLT 2	Executive mission review/The main reason	CLT1 + because of these key causal effects	+ provide backstories for key entities, spatial and temporal aspects of the mission; drill down the additional details for the critical selected mission aspects/ ~30s
CLT 3	Mission summary/The justification	CLT2 + because in the full causal model these paths are of	+ provide advisories and alerts related to changing context of mission as

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

		greatest importance (magnitude)	related to tasks at hand/~5min
CLT 4	Mission brief/the basis of justification	CLT3 + because here is the full measurement model	+ provide links to alternative planning and tasking if determined by context/~30min
CLT 5	Mission plan or report/A full summary of the data	CLT4 + because here is the time-step history of all the measurements	As supplied situationally to one of the levels above/~60min
CLT 6	Mission details/all the data	CLT5 + and here are all the anomalies and alternatives considered	As supplied situationally to one of the levels above/>60min

Table 1: Six layers of CLT for informational systems.

XAI plays a crucial role in enhancing communication within Human-Machine Teams by making AI systems more transparent and understandable to human operators [5,6]. Communication is crucial for team performance, as it helps develop shared mental models and supports essential team processes like planning. In human-machine teams (HMTs), communication is examined through transparency, which refers to how well a machine's interface allows a human to understand its intentions, performance, and reasoning. Although perfect transparency hasn't been achieved, machines are improving in their ability to share information and coordinate with humans, using features like turn-taking and language recognition to enhance communication [3].

[4] describes communication essential in teamwork, enabling teams to translate individual efforts into collective outcomes. Teams that effectively communicate and monitor performance in relation to shared goals tend to outperform those that lack such coordination. Beyond just sharing goals, it's crucial for teams to share the intent to achieve them, which directs individual actions toward team objectives. High-performing teams ask fewer but more efficient questions, push information proactively, and maintain situation awareness, helping to ensure that everyone is aligned and informed. Effective team processes, such as signalling shared intent, supporting shared mental models, and monitoring performance through communication, are vital for success. These principles, established in human-human teams, are likely applicable to human-machine teams (HATs) as well.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

In HAIKU, XAI aims to improve the explainability of AI models, allowing humans to comprehend the AI's intentions, performance, plans, and reasoning processes, which fosters trust and effective communication [7]. This is particularly important as machines utilising neural networks, while often high-performing, tend to struggle with communication due to their complex, distributed statistical representations. XAI helps bridge this gap by translating these representations into formats that humans can easily understand, thereby improving the bidirectional flow of information between humans and machines [5]. Ultimately, XAI is essential for creating more transparent, trustworthy, and efficient interactions within HMTs, contributing to better coordination and overall team performance [7].

The purpose of Task 5.2 is to generate a communication model and its mapping to the abstraction levels (the CLTs from D5.1) for each use case and validate it (Task 5.3) for UC-specific hypotheses.

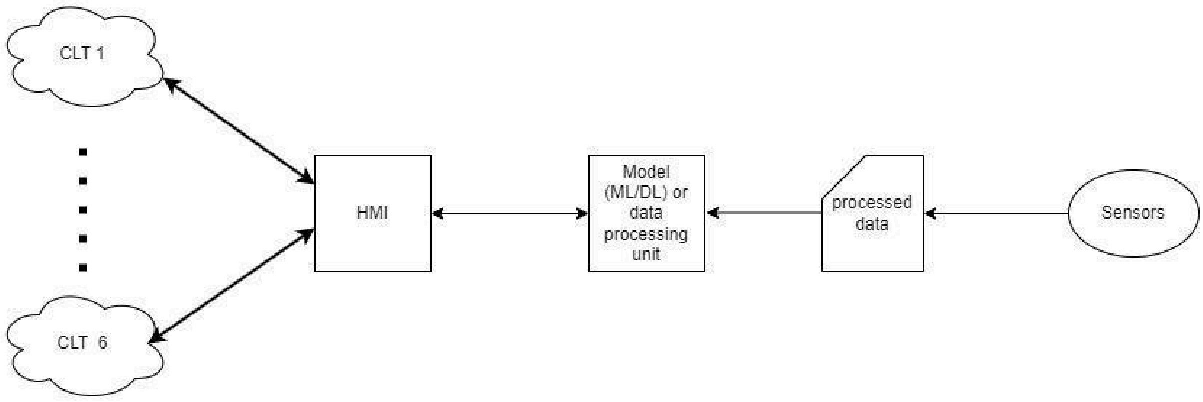


Figure 1: Communication model template for the use cases.

As the nature of use cases is different, a generalised approach was adopted, though it can be tailored to the specific nature of the use case (Figure 1). The purpose of the approach is to capture how data (from sensors) is transformed and mapped into the abstraction levels (CLTs) and, if possible, identify feedback loops, where the human and the intelligent assistant engage in cyclic interaction. Although it should be noted that a cyclic interaction may occur in the inner section of the assistant. Task 5.3 will proceed with the planned evaluation for the XAI strategy, the CLTs, and the communication model, namely, to examine if the approach captures the requirements for explainability, trust, transparency and team building between the human and the intelligent assistant.

After EASA published the second version of the AI roadmap in 2024, HAIKU use cases applied it to their assistant systems and tailored use cases specific explainability requirements. The detailed process is described in deliverable 4.1. These requirements are used in development and in the second validation study.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

In the next section of this deliverable, a description of how all the Use Cases implemented the CLT model to define their XAI Strategy is detailed. All the changes made to the CLT structure because of validation 2 are reported. A full overview of all the CLT implementation and the communication models is provided.

1. Use case 1: Flight deck startle response

1.1. Context

The FOCUS intelligent assistant aims to detect the startle and surprise reaction of pilots to be able to support them in recovering as quickly as possible. It aims to help pilots regain control of the aircraft and a good situational awareness to be able to stay "ahead of the aircraft". FOCUS is envisaged to play an active role when an unexpected event occurs and when a startle or surprise response is detected, providing support as long as necessary.

1.2. Construal levels

Generally, the adverse effect of a startle or a surprise does not last more than 5 minutes. According to the VAL 1 results and the progress of the development process, the CLT table for Use Case 1 was updated:

CLT Level	Applicability	Description
CLT 1	During operation	• Give information about the pilot's physiological state and their own situational awareness • Inform the pilot about assistant activation upon startle effect detection
CLT 2	During Operation	CLT 1 + : • Appearance/Disappearance of attention getters on interfaces. • Ambient light pulsing and haptic wristband stimulation
CLT 3	During Operation	CLT 2 + : • Information (e.g. colours) provided with attention getters

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

CLT 4	Post-OP briefing	CLT 3 + : ● Reasons for the appearance of attention getters ● Reasons for the startle effect detection
CLT 5	Post-OP briefing	CLT 4 + : ● Evolution of the situation awareness score ● Evolution of the physiological parameters
CLT 6	Post-OP briefing	CLT 5 + : ● Detailed debriefing on how the unexpected event was managed and analysis of the SA score and physiological parameters.

Table 2: Updated CLT table for use case 1.

Following VAL 2, the CLT table remained the same, as CLT 1 to 3 were all positively welcomed by participants. The CLT framework helped us propose designs and iterate on them between the two validation phases. For example, we removed the heart rate information from the EFB as it did not seem to provide useful information for the pilots, especially during the startle event and the few seconds following it. On the other hand, another sensory channel was used to draw attention to the most important events detected by FOCUS. Previously, only a red box was drawn around the deviating parameters, but in VAL2, an audio message was also emitted. This new design is also more in line with the existing cockpit philosophy.

1.3. Communication model

The processes in this UC are designed to detect the pilot's startle and surprise and keep their situation awareness on an acceptable level. It is important to note that the stress regulation function described in deliverable 4.4 is a response designed for the startle detection function.

The communication model for situation awareness is displayed here (Figure 2):

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

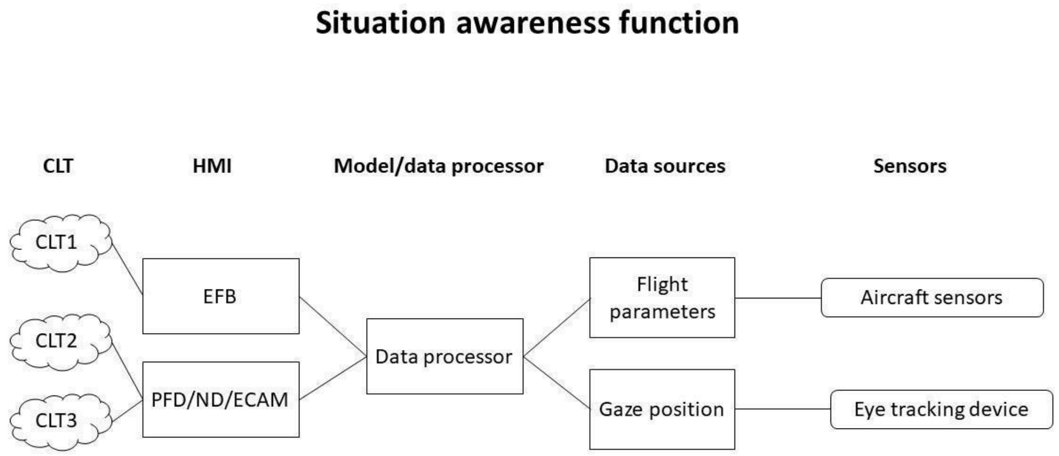


Figure 2: Communication model for situation awareness function

The sensors and hardware involved in this function are:

- ECAM
- PFD-ND
- Gaze (eye tracker)

The flight parameters (described in deliverable 4.4) are captured and evaluated by FOCUS (*Is the parameter above/below a specific threshold? Is the parameter varying too rapidly?*). In parallel, the gaze position, the duration and the timing of gaze on the interfaces are monitored.

The system evaluates if the pilot is aware of the evolution of the flight parameters, and in case s/he is not, it triggers attention getters of different colours which are mapped to CLT 2 and 3. Once the pilot looks at the highlighted parameters, the attention getters disappear.

The communication model for startle detection is displayed in Figure 3. The sensors and hardware include:

- PPG, ECG, GSR, EMG
- ECAM
- Haptic wristband
- LED lights for ambient light

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

The pilot's physiological data - including heart rate (in beats per minute), skin conductance, muscle activity, and respiration rate - serve as inputs for the startle module. This module outputs the pilot's state (e.g., startled/not startled, surprised/not surprised). When startle or surprise is detected, the system activates a haptic wristband, ambient lighting, and LEDs. The wristband vibrates at a frequency of 60 BPM, which seems according to a fundamental experiment done at ENAC to be the most effective for triggering an unconscious adaptation of the heart rate. Visual and haptic communication channels are therefore activated through this design.

In the initial design version, the pilot's heart rate was displayed on the Electronic Flight Bag (EFB) to enhance awareness of their physiological state. Communication relies on a combination of visual signals, such as ambient pulsing lights, and haptic feedback through the vibrating wristband.

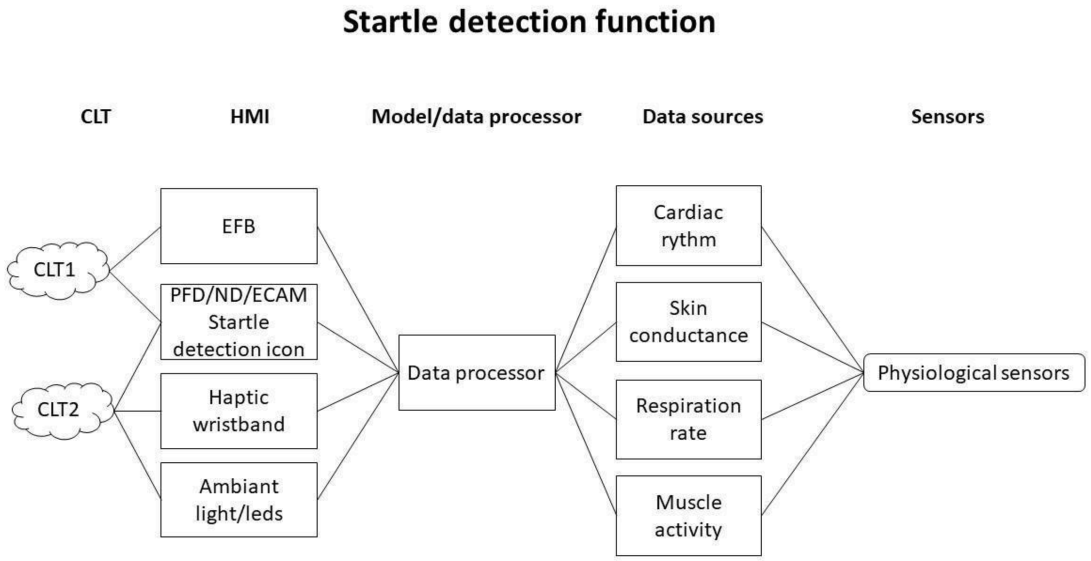


Figure 3: Startle detection communication model.

1.4. Validation 1

Validation 1 was a very useful step to collect feedback and insights to refine the design of FOCUS. Concerning the XAI strategies, the main aspects that emerged are:

- The red colour of the attention getters was deemed too strong, as, in the cockpit, red means an emergency.
- Too many attention getters on the interface may disturb rather than support situation awareness.

These aspects have been considered in the design and development process. A more specific validation of the XAI strategies and the communication models underneath is carried out in VAL2, where a targeted questionnaire is given to participants.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

1.5. Validation 2

During VAL2, the explainability of the “FOCUS” IA was tested. The set of explainability requirements selected for VAL 2 is shown in the following Table. In UC1, FOCUS delivers explanations during operations regarding the reasons behind the activation of attention getters generated by the Situation Awareness Augmentation Module. These explanations are conveyed through the colour coding of attention getters and a dedicated Human-Machine Interface (HMI) on the Electronic Flight Bag, which displays the pilot's situation awareness state in real time.

EASA-like EXP requirements for UC1
EXP-10: FOCUS must be able to provide different levels of explainability, based on user needs, for the Startle / Incapacitation Detection module, Stress Regulation module, and Situation Awareness SA augmentation module.
EXP-11: FOCUS explanations must be clear and understandable to the user, for the Detection module, Regulation module, and SA module.
EXP-12: FOCUS explanations must permit evaluation and assessment of system Detection / Regulation / SA augmentation) actions.
EXP-13: FOCUS must be capable of explaining its Detection/Regulation/SA augmentation) actions at different levels of explainability, and with progressive levels of detail.
EXP-15: FOCUS explanations must be presented with minimum delay, consistent with a startle event timeline.
EXP-16: FOCUS explanations, as presented on the EFB, must permit user-driven probing of CLT level) explanation details.
EXP-17: FOCUS must provide the user valid and reliable explanations, consistent with data inputs and outputs of the three modules (i.e. startle detection, stress regulation, and SA augmentation).
EXP-18: Training must include familiarisation with system I/O states, including correlation between input states and events (environmental startle events, pilot stress response) and system decisions and actions.

Table 3: EASA-like EXP requirements for use case 1

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

The VAL 2 activities, which were focused on explainability, involved administering questionnaires and collecting qualitative feedback through debriefing for EXP-10 to EXP-18, as outlined in the table above. The results from the questionnaires and debriefing sessions were used to assess participants' subjective perception and understanding of the CLT levels.

Following VAL 2, the main findings can be summarised as such:

- Too many eye-catching alerts on cockpit screens is not an acceptable design and that prioritisation of information highlighting is needed.
- To mitigate the distracting nature of the strong red alerts on the pilot flight display, participants suggested using auditory messages such as “speed!” to bring attention to the speed, as they are already used to such callouts done in today’s operations.
- Participants suggested that FOCUS could adapt itself to different piloting profiles, providing tailoring to FOCUS’s sensibility could increase Human-AI interaction.
- Information presented by FOCUS on the EFB couldn’t help the pilot understand FOCUS's status about the pilot’s SA. The EFB design should be improved to increase the pilot’s understanding of FOCUS behaviour.
- Most participants did not require additional explanations about what the assistant was doing or when. However, some participants expressed a preference for the assistant to clarify why it issued certain callouts and to prioritise them based on the context. One participant used the EFB to better understand and even anticipate the assistant's outputs, enhancing their situational awareness (SA).
- Participants suggested that the assistant’s callouts could be improved by considering potential corrective actions by pilots, in addition to accounting for gaze position.
- For all pilots, the warning callouts (red + audio) were the most relevant, Caution (based on time) was deemed less relevant.
- Only a few participants found the assistant’s actions distracting, and when distractions occurred, they were minor.
- Some participants asked to have an SA support based on the evolution of the deviation instead of the deviation itself. Doing so will lead to a support that is closer to what an experienced pilot monitoring could do.
- Many participants desired the assistant to go beyond its primary role of flight assistance. They wanted it to contribute to assessing and understanding the overall situation, for example, by using a structured decision-making process like FORDEC.

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

2. Use case 2: Flight deck route planning/replanning

2.1. Context

OlivIA (OperationaL Intentions adVIser for Aviation) is a decision-making support tool for pilots handling in-route threats and/or selecting alternate flight routes. Its purpose is to alleviate pilots' cognitive workload, enabling higher quality, holistic mission-focused decisions, in complex situations. It offers route adjustments prioritised and evaluated according to operational intentions. The tool also benefits the operations control centre, enhancing coordination and response times.

2.2. Construal levels

The main changes after VAL 2 are presented in the table below (Table 4):

CLT Level	Applicability	Description	Changes after VAL 2
CLT 1	During operation	• Intention: the interface displays the completion rate of each intention for a given trajectory in the form of a radar diagram. This rate is also displayed verbatim. • Trajectory: the interface shows a graphical representation of the trajectory, on a map, with the route the aircraft will take and the associated environmental constraints (weather, wind, turbulence).	• The radar diagram needs to be redesigned because some people are unable to interpret the information (illusion of 3D projection). • Some of the colours need to be changed because they are too close to each other, and the

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

			presentation of additional trajectories could be tested.
CLT 2	During Operation	CLT 1 + : ● Trajectory: the key performance indicators are presented in text form alongside the radar diagram on request. Only the 3 most significant are shown. ● Airport: the key performance indicators are presented in a pop-up window located in close proximity to the airport.	● No change planned for the KPIs representation. ● Information originally provided at CLT 3 will be integrated to CLT 2
CLT 3	During Operation	CLT 2 + : Trajectory: the other key performance indicators (KPIs), which are of lesser importance, are presented and an explanatory text is added to improve transparency. Airport: below the KPIs, a text describes the reason why this KPI has taken such or such value.	● No more CLT3 level after VAL2, the information in CLT3 can be at CLT2 level. All the information has been grouped together in CLT2.

Table 4: CLT levels for use case 2.

The CLT scheme originally proposed didn't seem to consider the complexity and heterogeneity of the information normally used for decision making. From VAL 2 observations, it seems that when pilots consider they need to analyse the data that substantiates the interpretation at the operational intentions level, they would prefer to quickly inspect all relevant supporting information. Even though this additional

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

information may be on different levels of abstraction, they are rather "close" to them in terms of cognitive distance.

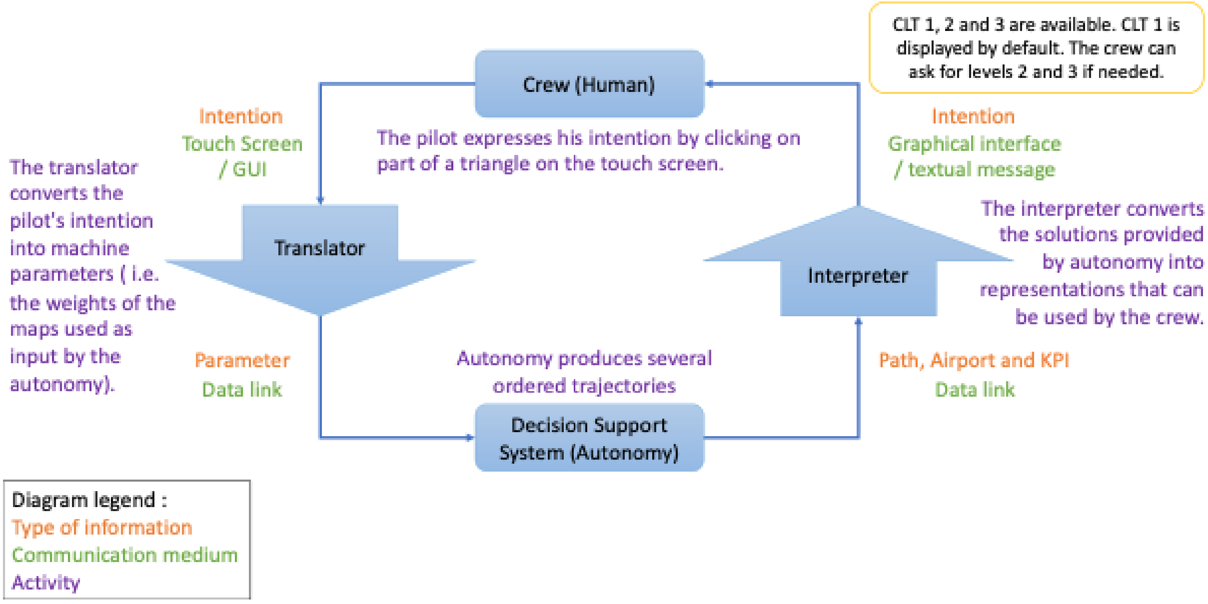
The CLT framework seems to be suitable for exploring the complexity of a situation description by increasing the level of refinement to improve situational awareness. Nevertheless, adaptability and context awareness to select the information to be displayed on each level could benefit communication.

2.3. Communication model

The special feature of OlivIA is COMBI, an interaction system to ease bidirectional communication between a human and an autonomous system. COMBI shifts the level of abstraction of language and focuses on communication in terms of intentions.

We can explain the principle of changing abstraction levels in the language using the SECI (socialisation, externalisation, combination, and internalisation) model. Nonaka and Takeuchi's SECI model is a theoretical framework developed to explain knowledge creation and management [10].

The different steps of decision-making with OlivIA support are summarised in Figure 4.



CLT 1, 2 and 3 are available. CLT 1 is displayed by default. The crew can ask for levels 2 and 3 if needed.

The pilot expresses his intention by clicking on part of a triangle on the touch screen.

The translator converts the pilot's intention into machine parameters (i.e. the weights of the maps used as input by the autonomy).

The interpreter converts the solutions provided by autonomy into representations that can be used by the crew.

Autonomy produces several ordered trajectories

Figure 4: Description of the usage of OlivIA in the use case and its implementation in terms of interfaces and the type of data exchanged in VAL 2.

OlivIA improves understanding and communication and creates knowledge for humans about the system and the environment in which they make increasingly relevant decisions. More pragmatically, OlivIA is used in use case 2 to enable the crew to replan a route to an alternate after the closure of an airport:

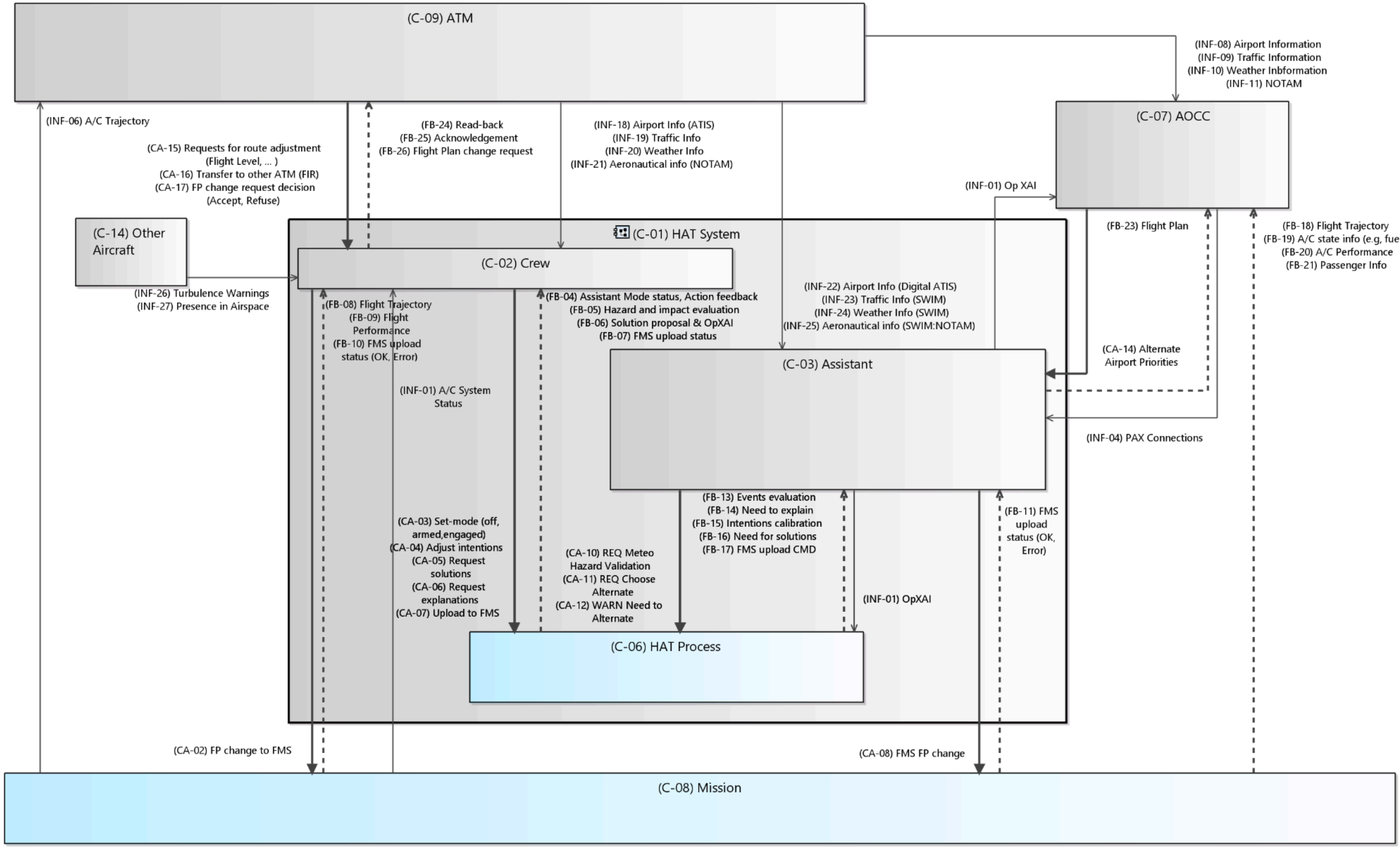
This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

- At their initiative, the users indicate to the meta-solver their priorities in terms of intentions. In this step, the pilot estimates how the problem should be solved, expressing their intention by prioritising three issues: their own cognitive comfort (the "simplicity" of the proposed solution), the comfort of the passengers, or the profitability of the airline. This input is provided to OlivIA with a single click on a tactile interface (touchscreen display) between the Navigation Display (ND) and the Electronic Centralised Aircraft Monitor (ECAM). This interface is described in more detail in deliverable 4.5.
- At a second step, the COMBI downward translator converts this intention into a machine parameter (a matrix of weights) which can be used to weight the input parameters of the trajectory proposal model.
- At a third step, OlivIA calculates trajectories from weights given as input parameters, which it applies to various data obtained from the environment, such as the weather (precipitation, wind, turbulence, etc.), air traffic, the status of destination airports, etc. OlivIA selects the 3 solutions that are closest to the request expressed by the pilot. Each of these is constituted by a combination of an airport and an associated trajectory.

- At the final stage, COMBI's upward translation brick takes the solution and generates:
    - a graphical representation of the trajectories.
    - a schematic representation of the pilot's intentions and an explanation of how these intentions are achieved by the solutions.
    - explanations in the form of descriptions/interpretation of the KPIs related to pilots' intentions.

This presentation of the information is intended to be consistent with how the pilots have expressed their intentions, but also with how they understand the problem, and the explanation is intended to be easy to understand. In terms of information and communication flows, we are using a model based on the Systems Theoretic Process Analysis (STPA) method. Figure 5 provides an exhaustive list of all the information exchanged. The information can come from 4 different sources: Air Traffic Control (ATC), the Airport Operation Control Centre (AOCC), the aircraft and other aircraft.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332



This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Figure 5: A preliminary STPA model has been developed to analyse the incoming and outgoing flows of the autonomy brick. The bold black arrows represent instructions or orders, the dotted arrows represent feedback, and the thin solid arrows represent information flows. Communication is mediated through the "HAT Process", C-06, in blue. The process being controlled is the aircraft mission (C-08). The HAT System is composed of the Crew (C-02) and Assistant (C-03).

From ATC:
- Airport information
- Traffic information
- Weather information
- NOTAMs (voice)
- SWIM: weather information
- SWIM: aeronautical information (NOTAM, ATIS, etc.)

From AOCC:
- Alternate airports priorities
- PAX connections

From aircraft:
- Weather Radar Information
- Flight trajectory
- A/C state information (e.g. fuel, failures, etc.)
- A/C performance

From other aircraft:
- Turbulence warnings
- Presence in airspace

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

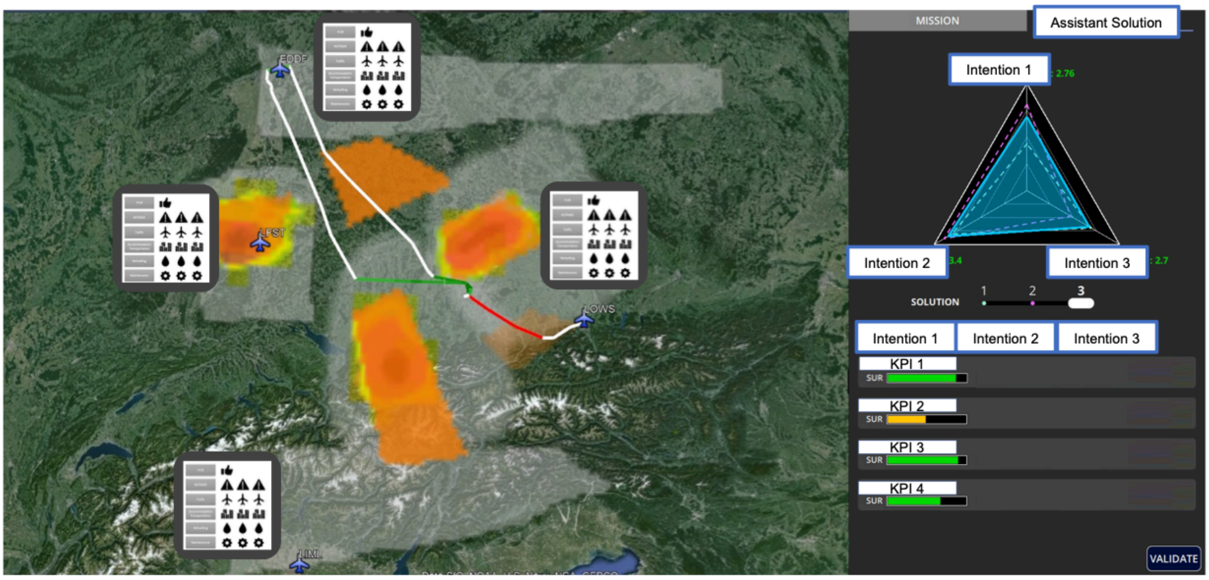


Figure 6: HMI prototype for validation 2 at CLT2 explainability level. On the left, maps showing trajectories and airports. On the right, explainability is linked to intentions and associated KPIs.

Figure 6 shows the prototype of the HMI that was used for Validation 2. The first two levels of explicability are shown.

2.4. Validation 1

UC2 will validate the level of explainability and the communication process during VAL2. The HMI will be situated in a central position in a simulator cockpit (between the PFD/NDs of the pilots and co-pilots). The objective is to ascertain whether the information presented on the interface facilitates more effective decision-making, as evidenced by reduced time to completion and enhanced situational awareness.

To validate CLT levels, activity traces will be employed. To advance from CLT 1 to 2, the pilot must click on the interface, and the same is required for progression from CLT 2 to 3. Thus, by identifying the level at which the pilot has consulted the explainability interface, it is possible to ascertain the CLT necessary and sufficient for the diversion. This result will be validated through a self-confrontation interview following the experiment.

To validate the change in abstraction levels (SECI model), we are comparing the mental representation of the situation of pilots who have used COMBI with those who have not in the same scenarios. In addition, we will consider other indicators such as the relevance of the solution chosen and the decision-making time. This analysis will also be confirmed during the self-confrontation interview at the end of the experiment and qualitative feedback by questionnaire, for example, on fatigue and mental workload.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

2.5. Validation 2

The main findings can be summarised as such:

- Primarily, the interaction concept that was validated in VAL1 confirmed the significance of offering pilots a range of suggested options during decision-making processes, as opposed to single recommendations. This approach supports user agency and avoids the perception of automation as overly directive.
- Secondly, the findings from VAL 2 highlighted the necessity of multi-level explainability, with different pilots expressing varying preferences, some favouring high-level summaries while others requiring access to detailed operational information, such as weather data (e.g., METAR). These differences underscore the necessity for adaptable explanation strategies to align with individual user profiles. Additionally, abstract, high-level summaries, though intended to reduce cognitive load, were frequently perceived as too generic to be actionable, particularly when system performance was evaluated across diverse dimensions (e.g., passenger comfort, pilot cognitive load, and company profitability).

- Finally, the evaluation of the CLT-based proposed solution suggested that while it provided a useful structure, it was ineffective in meeting the pilots' operational needs and preferences. This highlights the importance of more flexible and context-aware explanation mechanisms.

The set of explainability requirements for use case 2 is in the table below:

EASA-like EXP requirements for UC*2*
EXP-10: IA must be able to explain both its reroute- and airport diversion recommendations using progressive CLT levels.
EXP-11: IA must provide explanations in a clear and unambiguous form
EXP-12: IA must provide explanations relevant to the assessment of the appropriateness regarding expected decision / action
EXP-13: IA must provide explanations at the level of operational intentions along with each proposed solution.
EXP-16: IA interface must provide the Pilot the ability to navigate, for each proposed solution, through three different layers of explanations.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

EXP-17: IA must provide timely, relevant and valid explanations to the Pilot about each proposed solution.

Table 5: EASA-like explainability requirements for use case 2.

The VAL2 activity performed for explainability consisted mainly of collecting and processing pilots' evaluation of the explanations provided in the experiment, their role in improving pilots' SA, workload and trust in the system, and the overall usability of the explainability strategy. VAL2 results contributed to planning further improvements for the UC2 Explainability Strategy and Communication Model.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

3. Use case 3: Urban Air Mobility

3.1. Context

The Digital Assistant for UAM Coordinator (DUC) oversees Urban Air Mobility (UAM) and urban airspace (i.e., U-space) operations, ground events, and city life. It assists the Human UAM Coordinator with daily tasks, including planning and emergency response, such as in-flight medical incidents, conformance monitoring, and ground events affecting the urban airspace and its users. By providing real-time support, the DUC reduces the UAM Coordinator's workload, improves their situational awareness to allow them to focus on strategic decision-making. This collaboration enhances operational efficiency, improves safety, and ensures effective oversight of UAM activities, ultimately facilitating smooth coordination of urban airspace.

In regards to XAI, the explainer functionality provides explanations for DUC's actions or recommendations, delivered in a flexible format (e.g., through storytelling with visual animations and narration). The goal in VAL2 with respect to Storytelling/Text explainer is to explore and evaluate the use of storytelling and text formats as a method for explaining how AI-based intelligent assistants operate and derive specific outputs, particularly within the context of Urban Air Mobility (UAM). The validation aimed to design explanation mechanisms that cater to end users, such as UAM Coordinator (in the case of validation- ATCO), who may have limited technical knowledge of AI and machine learning models. By adopting a user-centered approach, the research seeks to enhance human-AI teamwork by ensuring that explanations are understandable, foster trust, and facilitate better decision-making.
A storytelling/text explanation was triggered by a specific event occurring in the simulation (also referred to as Scenario 2 - Fire Emergency in D6.4). To create the Storytelling explainer, we used a series of iterative design sessions where the designed storytelling explainer was tested and discussed. In the design process, a designer focused on the storyline creation, story elements visualisation and changes implementation. Additionally, experts within the ATM and UAM domain advised on what to include in the storytelling explainer, such as what DUC should consider while deciding for closing parts of U-space during fire. Technical experts were involved to enable the connection of the storytelling explainer with the simulator and make it synchronised and timed with the produced scenario, meaning that the explanation was shown while the simulation kept playing, i.e., the simulation was not paused.

Two research questions were defined for VAL2:

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

- *How does the mode of explanation (storytelling vs. textual) influence operator attitudes, comprehension, and decision in response to decision recommendations made by DUC?*
- *How does the application of different CLT structured explanations through interactive visual storytelling impact the perceived transparency of DUC? '*

3.2. Construal levels

The application of the CLT framework in VAL2 is outlined in the table below. It is important to note that only CLT1 through CLT3 were implemented in UC3. CLT4 to CLT6 were excluded, as they were considered unsuitable (during the design process and early testing). Levels CLT4 to CLT6 were excluded due to the urgency of the operational task, which requires quick decisions and the length and complexity of deeper explanations, which were not feasible in this time-sensitive setting (Table 4).

CLT Level	Applicability	Description
CLT 1	During operation	● *Executive summary*: immediate perception ● Overview of the fire situation ● Indication of the number of traffic influenced for geofence A and B ● Indicating that the weather was an important factor
CLT 2	During Operation	● *Mission overview:* situational trade-offs ● Wind direction and speed are introduced as the primary factors influencing DUC's risk assessment and the shape and size of the geofence zones. ● Other factors are presented visibility, fire type, impact on the vertiports, impact on the traffic)
CLT 3	During Operation	● *Mission summary:* analytical comparison ● The prediction time is set to 30 minutes. ● Weights of factors are presented Geofence A: Fire/smoke type (40%), wind direction and strength (20%), visibility (10%), traffic affected by volume of geofence zone (30%), etc. Geofence B: fire/smoke type (40%), wind direction and strength (40%), visibility (10%);

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

		traffic affected by volume of geofence zone (10%) etc. ● Classification of fire is presented

Table 6: CLT levels for use case 3.

What worked well:

1. CLT 1 (Executive summary)
    - Effectively served as a clear and accessible introduction to DUC's reasoning process.
    - Highly rated for providing a strong foundational overview of DUC's reasoning process.
    - Helped orient participants to the decision-making context.
2. CLT 2 (Mission Overview)
    - Considered the most appropriate level for decision-making in the fire emergency scenario.
    - Struck a good balance in length and level of detail, presenting all relevant factors without overwhelming the user.
    - Well-suited for operational use where quick, informed decisions are needed.
3. CLT 3 (Mission Summary)
    - Enhanced understanding for some users, particularly around DUC's recommendation rationale (e.g., option A & B).
    - Provided valuable reinforcement for users who wanted deeper insights.
    - Supported layered learning by building on earlier CLT levels.
4. Overall Progressive Structure (CLT 1 → CLT 2 → CLT 3)
    - Demonstrated an effective scaffolded approach to explanation.
    - Each level progressively deepened the user's understanding.

What did not work well:

1. CLT 1 limitations
    - Some users felt it lacked sufficient detail for making confident decisions.
    - Users expected more substantive reasoning earlier in the process.
2. CLT 3 redundancy
    - Perceived by some participants as repetitive and offering diminishing value.
    - Needs refinement to ensure it contributes distinct, non-redundant information.

Proposed Changes and Recommendations:

1. Refine CLT 3

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

    - Reduce the overlap with CLT 2 and make content more targeted and uniquely informative.
    - Avoid unnecessary repetition while still adding value.
2. Integrate key decision factors earlier
    - Consider moving critical elements (e.g., geofence weighting, wind impact) into CLT 2 to support decision-making for users who may not continue to CLT 3.
3. Introducing hybrid or visual summary formats
    - Explore combining video and text elements to accommodate different user preferences.
    - Develop concise visual summaries to support faster comprehension and retention.

These lessons suggest that while the CLT framework is broadly effective, especially in a progressive format, optimising the level of detail and timing of information delivery is key to improving decision support in high-stakes UAM scenarios.

3.3. Communication model

In use case 3, the communication model centres on a single, time-critical decision-making process triggered by an emergency event, such as a fire at a vertiport. Although the DUC does not yet incorporate AI or machine learning, it simulates how data can be processed and communicated to provide clear, structured explanations to the UAM Coordinator. The communication model is shown in the figure below. (Figure 7):

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

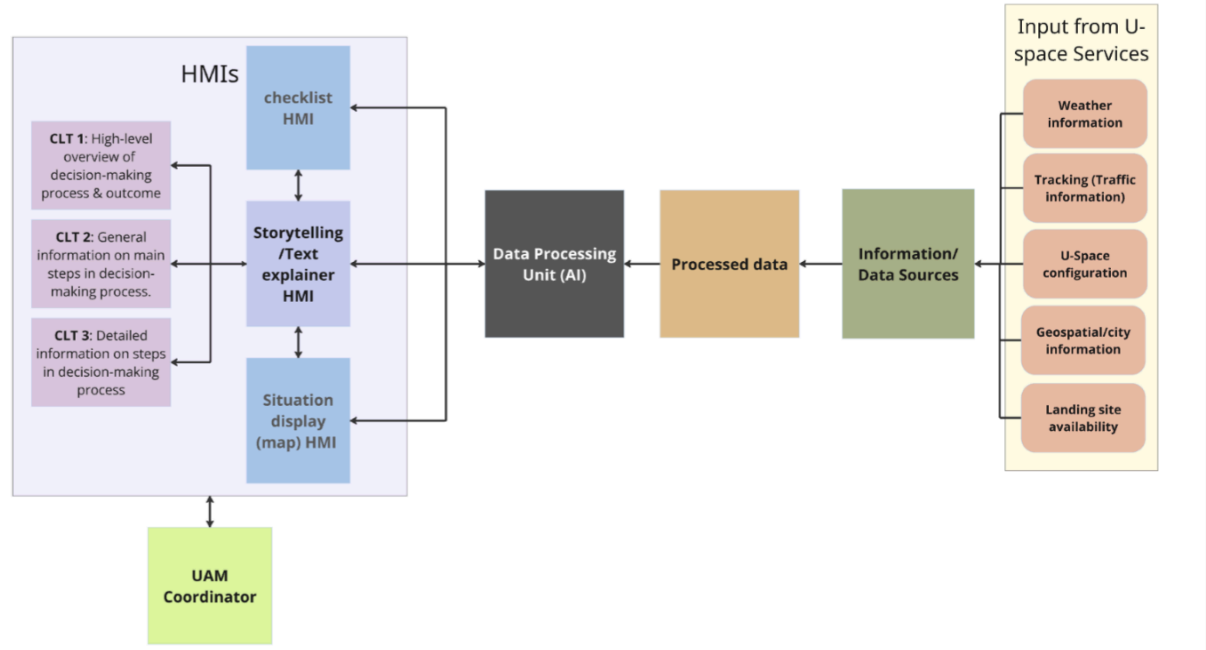


Figure 7: The communication model for use case 3.

At a conceptual stage, the system gathers data from multiple sources (input from U-space services), including weather, traffic, geospatial inputs, and human reports, and processes this through a data processing unit. The outputs are communicated to the human operator through three HMIs:

- U-space Interface HMI (Situation display): A map-based operational overview that can be used to visualise decision options as graphical overlays directly on the map. Directs the UAM Coordinators attention to the explainer HMI.
- Explainer HMI: Delivers structured explanations using the CLT framework.
- Checklist HMI: Directs the UAM Coordinators attention to the explainer HMI.

This layered explanation approach ensures that operators understand not only what is happening, but also why it is happening, enhancing transparency and supporting trust in automated U-space decisions. The communication process between DUC and the UAM Coordinator made use of the following modalities:

Storytelling Explainer:

- Visual: Animated overlays showing fire location, geofencing, airspace impact, traffic flows.
- Interactive: Checklists, confirmation buttons, CLT-level navigation (next/pause).
- Audio: Narration synchronized with visuals, guiding the user through each CLT level.

Text Explainer:

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

- Textual: All content is presented in structured text using bullet points, tables, and headings corresponding to CLT levels.

The following table 8 lists the inputs to the explainer. These modalities were conceptually identified and scripted in VAL 2, and have not been implemented in a working prototype.

Input Source	**Capture & Processing**	**Communication Modality**
Weather Data	Real-time feeds (e.g., wind, temperature)	Numeric, text, map overlays
Traffic Data	UAM flight positions, speeds, plans	Text, numeric tables, spatial overlays
U-space Configuration	Geofences, no-fly zones, altitude limits	Databases, visual boundaries
Geospatial Data	Population, vertiport locations, obstacles	Numeric and map-based visualisations
Emergency Stakeholder Input	Initial reports from ground operators (voice/text)	Transcribed text or checklist inputs
User Interaction (UAM Coordinator)	Checklist inputs, confirmation, fire cause selection	Clicks, HMI interactions

Table 7: inputs to the explainer

The following table lists the outputs of the explainer:

Output Element	**Description**	**CLT Level**	**Modality**
Fire Situation Overview	Summary of fire type, location, smoke spread, airspace impact.	CLT1	Visual animations, narration

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Geofence A & B Options	Two proposed no-fly zones with shape/size influenced by wind, traffic, safety.	CLT2	Visual animations, narration
Factor Weight Breakdown	For each geofence, breakdown of influence weights (e.g. fire 40%, wind 20%).	CLT3	Visual animations, narration
Traffic Impact Estimation	Number of vehicles affected by each geofence.	CLT2	Visual animations, narration
Risk Assessment Rationale	Logic behind geofence shape (e.g., wind direction spreading smoke northwest).	CLT3	Visual animations, narration
Recommended Action	Final options for UAM Coordinator to select.	CLT1	Visual animations, narration

Table 8: outputs of the explainer

3.4. Validation 1

During VAL1, CLT levels 1-4 were applied to the storytelling explainer for the UAM Coordinator. The application of these levels was found to be effective, as participants confirmed that the levels of detail were appropriate and that the presented concepts were understandable and easy to grasp. This suggests that CLT helped the UAM Coordinator in navigating the scenario and understanding the events as they unfolded. The participants' positive feedback indicates that the use of CLT contributed to their comprehension of the DUC's decision-making process, enhancing their ability to make informed decisions during operations.

The plan for VAL2 is the following:

- Testing Higher Levels of CLT. Future research will involve developing and evaluating storytelling explanations that incorporate CLT levels 5 and 6. This will help determine the suitability of these higher levels of detail for various user needs and contexts.
- Enhancing Interactivity. A key area for improvement identified by participants is the need for more interactive storytelling explainers. Future studies will explore methods to make storytelling more interactive, such as allowing users to request explanations on demand by clicking icons in the pop-up window.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

- Customisation of Explanation Level of Abstraction. Tailor the level of abstraction of explanations according to the task, situation, trust level, and expertise of the user. This customisation will ensure that the explanations are appropriate and useful for different users and situations. If the XAI system is adaptable, enable users to customise the level of detail in the explanations they receive. This adaptability will allow users to select the explanation complexity that best suits their immediate needs and preferences.

3.5. Validation 2

DUC's XAI was designed according to the following requirements, which were then tested during VAL2:

EASA-like EXP requirements for UC3
EXP-10: DUC must be able to explain its decisions and recommend/ stations) using progressive CLT levels, for its recommended actions.
EXP-11: DUC explanations must be presented using a combination of text, symbols, and graphical overlays on the map display
EXP-12: DUC should be able to explain why different solution alternatives are proposed, including factors considered and how relevant they are, and the underlying decision making process.
EXP-13: DUC must present its decision-making rationale both prior to, and during situations, CLT. Prior explanations shall rely on a storytelling approach, concurrent explanations shall use a combination of text, symbols, and graphical overlays on the map display.
EXP-14: DUC must provide dynamic adaptation of explanation levels, per CLT.
EXP-15: Explanations prior to a situation (for training purposes) are timed to appear during periods with little activity. Explanations for decisions/actions in time-critical situations are timed to occur when DUC has derived a solution. The explanation is valid if the proposed decision/action is valid.
EXP-16: The system must retain a user-selectable explanation level (according to CLT), for all explanations provided by DUC.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Table 9: EASA-like explainability requirements for use-case 3

A human-in-the-loop simulation was conducted to empirically validate the Storytelling explainer. In the simulation, it was compared against a control condition, consisting of a text explainer. The VAL2 validation activities for the Storytelling Explainer were conducted alongside other VAL2 tasks, detailed in deliverable D6.4. The simulation tested the explainer with nine air traffic controllers (ATCOs) from Malmö ATCC, LFV Sweden. Each participant took part in a three-hour session. Their ages ranged from 26 to 57 years (M = 41.2, SD = 11.7), and their experience ranged from nearly 2 to over 30 years (M = 15.6, SD = 10.7). All were currently working as en-route controllers, with some also having experience in TMA, Tower, and procedural operations. While all had basic training in Urban Air Mobility (UAM), none had prior exposure to HAIKU, UAM, DUC, or the UAM Coordinator.

The simulation setup featured a prototype of the UAM Coordinator workstation with three large screens connected to a laptop. These screens displayed a checklist library (left screen), a situation display showing the Stockholm U-space map (center screen), and the Explainer (right screen), which played video-narrated explanations (Storytelling condition) or presented identical explanation in a text format (Text condition) supporting the DUC’s recommendations during a simulated fire emergency. The IA DUC system integrated scripted events and Wizard of Oz techniques.

The explainer was part of the "Fire Emergency" scenario (Scenario 2 in D6.4), involving a fire at an oil tank requiring closure of a nearby vertiport. The DUC presented two no-fly zone options and guided the UAM Coordinator to the explainer for the rationale behind each. Participants had to choose between the two options. Two formats of the explainer were tested: **storytelling (narrated video)** and **text.** Both formats contained identical information. Each participant experienced both formats in different orders to avoid order effects. Each session lasted 10–15 minutes.

Participants underwent a briefing, signed consent, completed a demographic questionnaire, and received a 20-minute training session on the simulator that included a portion on how to view and interact with the explainer functionality. Before viewing the explanation, participants made a preliminary decision. The explainer followed a three-step structure based on the Cognitive Load Theory (CLT), with increasing detail at each level. Participants could opt out of progress but were encouraged to view all levels for feedback purposes.

After each session, participants completed a format-specific questionnaire measuring understanding, trust, user experience (UEQ), explainability (Hoffman scale), situational awareness (SART), and decision confidence and satisfaction. Structured interviews gathered qualitative feedback on format preferences and clarity. This scenario aimed to address multiple human factors and explainability requirements (HF-08; EXP-10 - EXP-16).

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Quantitative data were analysed using descriptive statistics and visualisations. Due to the small sample size and ordinal data type, the Wilcoxon signed-rank test assessed differences between paired responses, and medians with interquartile ranges described central tendencies and variation.

Three scenarios were included in VAL 2, which took place in the Stockholm U-space area, which was developed and implemented from scratch on the UTM City platform to create the UATM HMI. Explainability was tested only in scenario 2. The explainer used in this study did not rely on AI. Instead, all explanation content was written (scripted) in advance by experts, using domain knowledge, and principles of design. The explanation content was crafted by subject matter experts who translated system recommendations into user-understandable narratives. This involved:

- Identifying key elements of each recommendation (e.g., decision rationale, potential impact on U-space users, and relevant geofence constraints).
- Structuring the content to address both why a recommendation was made and how it impacts the operational environment.
- Ensuring that explanations supported operator comprehension, decision-making, and awareness of system behaviour.

To optimise clarity and cognitive efficiency, explanations were structured using three levels of CLT. While the explanation content was identical in both versions, the way the information was presented varied:

- **Text format:**
    - Presented explanations in written form, structured according to the selected CLT level.
    - Enabled users to read at their own pace, revisit information, and reflect on content.
- **Storytelling video format:**
    - Narrated explanations using animated visuals synchronized with a voice over.
    - Each video corresponded to a specific CLT level, integrating visuals and reinforcing comprehension.

The scenario in this validation plays as follows:

- A fire erupts in an oil storage tank at Värtahamnen, spreading dense black smoke (250m high)
  → *DUC is not yet aware; no data acquired.*
- Nearby electric cars burn, increasing smoke density and toxicity
  → *No action from DUC yet; no input received.*

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

- Ground handler at Värtahamnen Vertiport spots the fire/smoke; informs Vertiport Manager
  → *Human communication begins; DUC still unaware.*
- Vertiport Manager decides to close the vertiport and submits emergency closure form to CIS
  → *DUC receives initial structured data via CIS: name, location, closure reason (emergency), unspecified fire location.*
- Vertiport status on U-space situation display updates to 'closed due to emergency'
  → *DUC detects update and suggests "Unexpected Vertiport Closure" checklist.*
- Vertiport Manager informs UAM Coordinator directly about the fire/smoke
  → *UAM Coordinator becomes context-aware; shares info with DUC via checklist inputs.*
- UAM Coordinator confirms checklist, selects 'fire/smoke' as cause
  → *Triggers DUC's "Vertiport Closed due to FIRE/SMOKE" logic; DUC starts processing relevant tasks.*
- UAM Coordinator contacts Emergency Response Unit for fire location and smoke spread
  → *DUC waits for geo-contextual data.*
- UAM Coordinator adds fire location and smoke information into the checklist
  → *DUC updates internal knowledge and builds shared awareness.*

CIS disseminates this information to other U-space stakeholders
→ *DUC receives confirmed location and impact zone.*

DUC's actions and explanation of geofencing options:

- DUC provides an overview of the fire situation
- DUC presents two no-fly zone options: Geofence A (small) and Geofence B (large)
  → *Both are shown visually on the UAM situation display.*
- DUC explains number of UAM traffic operations impacted by each zone
  → *Estimates are shown per geofence.*
- DUC explains core risk assessment logic
  → *Primary factor: wind direction and speed — key drivers of smoke spread and shape of no-fly zones.*
- DUC also considers secondary factors:
  - *Visibility reduction due to smoke*
  - *Fire type and volatility (oil + EV fires = high risk)*
  - *Impact on nearby vertiports*
  - *Impact on UAM traffic affected by geofence size*

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

- Prediction time set at 30 minutes
  → *DUC models fire/smoke spread for 30-minute future state.*
- → *Classification of fire is presented (type: oil + electrical vehicle fires; high-smoke output).*
- DUC displays factor weightings used in risk scoring:
  - *Geofence A (larger, round zone):*
    - Fire/smoke type: 40%
    - Wind direction/strength: 30%
    - Visibility: 10%
    - Traffic impact (volume): 10%
    - Vertiport impact: 10%
  - *Geofence B (smaller, elliptic zone):*
    - Fire/smoke type: 40%
    - Wind direction/strength: 30%
    - Visibility: 10%
    - Traffic impact: 10%
    - Vertiport impact: 10%

DUC invites the UAM Coordinator to choose between Geofence A or B
→ *Decision support, not decision-making.*

The goal in VAL2 with respect to Storytelling explainer is to explore and evaluate the use of storytelling as a method for explaining how AI-based intelligent assistants operate and derive specific outputs, particularly within the context of Urban Air Mobility (UAM). The validation aimed to design explanation mechanisms that cater to end users, such as UAM Coordinator (in the case of validation- ATCO), who may have limited technical knowledge of AI and machine learning models. By adopting a user-centered approach, the research seeks to enhance human-AI teamwork by ensuring that explanations are understandable, foster trust, and facilitate better decision-making.
A storytelling explanation was triggered by specific happening occurring in the simulation. To create the Storytelling explainer, we used a series of iterative design sessions where the designed storytelling explainer was tested and discussed. In the design process a designer focused on the storyline creation, story elements visualization and changes implementation. Additionally, experts within the ATM and UAM domain advised on what to include in the storytelling explainer, such as what

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

DUC should consider while deciding for closing parts of U-space during fire. Technical experts were involved to enable the connection of storytelling explainer with the simulator and make it synchronized and timed with the produced scenario, meaning that explanation was shown while the simulation kept playing, i.e., the simulation was not paused.

The lessons learned from both validation studies:

- **Enable user control over explanation depth and format.**
  Users should be given the flexibility to choose how much explanation they want to engage with, depending on their time constraints, workload, and prior understanding. Storytelling video was preferred by 90% of participants and perceived as clearer, easier, and more user-friendly, while text was seen as more neutral, sometimes slow or complex. Both formats had mixed reviews regarding engagement (e.g., boring vs. interesting), underscoring the need for user-driven control over format and detail.
- **Structure explanations according to CLT.**
  Explanations should support gradual exploration of content. Among tested structures, CLT2 proved most effective in helping users understand recommendations across both text and video formats. CLT1 lacked sufficient depth, while CLT3 overwhelmed users with too much information. A balanced level of detail, as seen in CLT2, optimally supports comprehension.
- **Use multiple explanation formats to support diverse user needs**.
  Different formats serve different cognitive and operational purposes. Visually narrated storytelling videos improve clarity, user satisfaction, and understanding, especially for concepts like geofences, where video received only positive ratings. However, text allows for self-paced reading and better management of cognitive load. Participants trusted both formats equally, showing that each can be credible and persuasive depending on context.
- **Evaluate storytelling formats for operational suitability.**
  While video explanations may enhance understanding, especially in non-urgent contexts, their effectiveness in fast-paced, high-stakes environments remains uncertain. Further research is needed to determine whether storytelling formats are practical and where time efficiency and rapid comprehension are critical.
- **Treat explainability as an interactive, user-driven process.**
  Explanations should not be static or one-size-fits-all. Instead, they should function like a dialogue, allowing users to ask follow-up questions and explore content at their own pace and depth. This dynamic approach better supports varying information needs over time.
- **Personalize explanations to user preferences and comprehension levels.**

The value of an explanation lies in whether the user feels it made sense. Some users found text harder to follow or less engaging, highlighting the importance of tailoring

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

explanations to individual cognitive styles, preferences, and familiarity with the content. Personalized formats increase clarity, relevance, and overall effectiveness.

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

4. Use Case 4: Digital and Remote Tower

4.1. Context

UC4 is developing ISA, an Intelligent Sequence Assistant to support tower controllers during high traffic, by optimising runway usage and ensuring safe and efficient operations. The IA can suggest traffic sequences, optimise inbound and outbound flows, and reduce stress and the risk of errors through the Explanation Generation Module, which is detailed in D4.2 and D4.5. In brief, this module takes as input a series of sequence calculations and outputs comprehensive textual explanations tailored to meet the diverse needs of ATCOs, offering various levels of detail as defined by the CLT framework. These explanations are displayed on the HMI, providing support for ATCOs in their decision-making processes.

4.2. Construal levels

The CLT table for UC 4 is the following:

CLT Level	Applicability	Description
CLT 1	Pre-Op/During operation	● Overview of the expected traffic (arrivals and departures, workforce during peak hours). ● If Pre-Op, can be used to brief ATCOs before work shift. ● KPIs with current situation.
CLT 2	During Operation	CLT 1 + : ● Display immediate solution for a sequence change (e.g. maps, updated flight maps etc.)
CLT 3	During Operation	CLT 2 + : ● Provides complete information for the changes, and the differences with the initial KPIs. ● Provides necessary alerts for the ongoing event.
CLT 4	Post-OP	CLT 3 + : ● Provides useful information regarding the event (changed sequence, essential sensor data) for debriefing for the next shift.

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Table 10: CLT levels for use case 4.

No changes were made to the CLT levels. Overall, the application of the CLT framework to the design of operational XAI interfaces has been very useful. It offers a flexible structure for presenting layered explanations, enabling users to access information at varying levels of abstraction depending on context and need. A key lesson learned is that CLT2, which conveys the immediate reason behind AI suggestions, is central to user engagement and trust, particularly when paired with interaction mechanisms such as mouse-hover for quick access. The model also shows promise beyond real-time use, offering potential in training contexts by helping operators gradually build an understanding of AI behaviours. In future projects and iterations of ISA, the model could be extended through multisensory interface design and adaptive systems capable of assessing mental workload to dynamically adjust the level of explanation, ensuring optimal cognitive alignment throughout operations.

4.3. Communication model

The communication model for this use case is limited to a single process related to the sequence generator (Figure 8). In the general picture, the assistant is fed the data generated from the simulator. This includes everything related to the aircraft in progress (from flight plan data, e.g. aircraft type, wake turbulence, origin, destination, standard departure, etc., to position data, altitude, instructions). These data are constantly processed by ISA, and any changes in estimated times, taxiing instructions, takeoff or landing, position variations, etc., can generate a new sequence (Table 11).

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

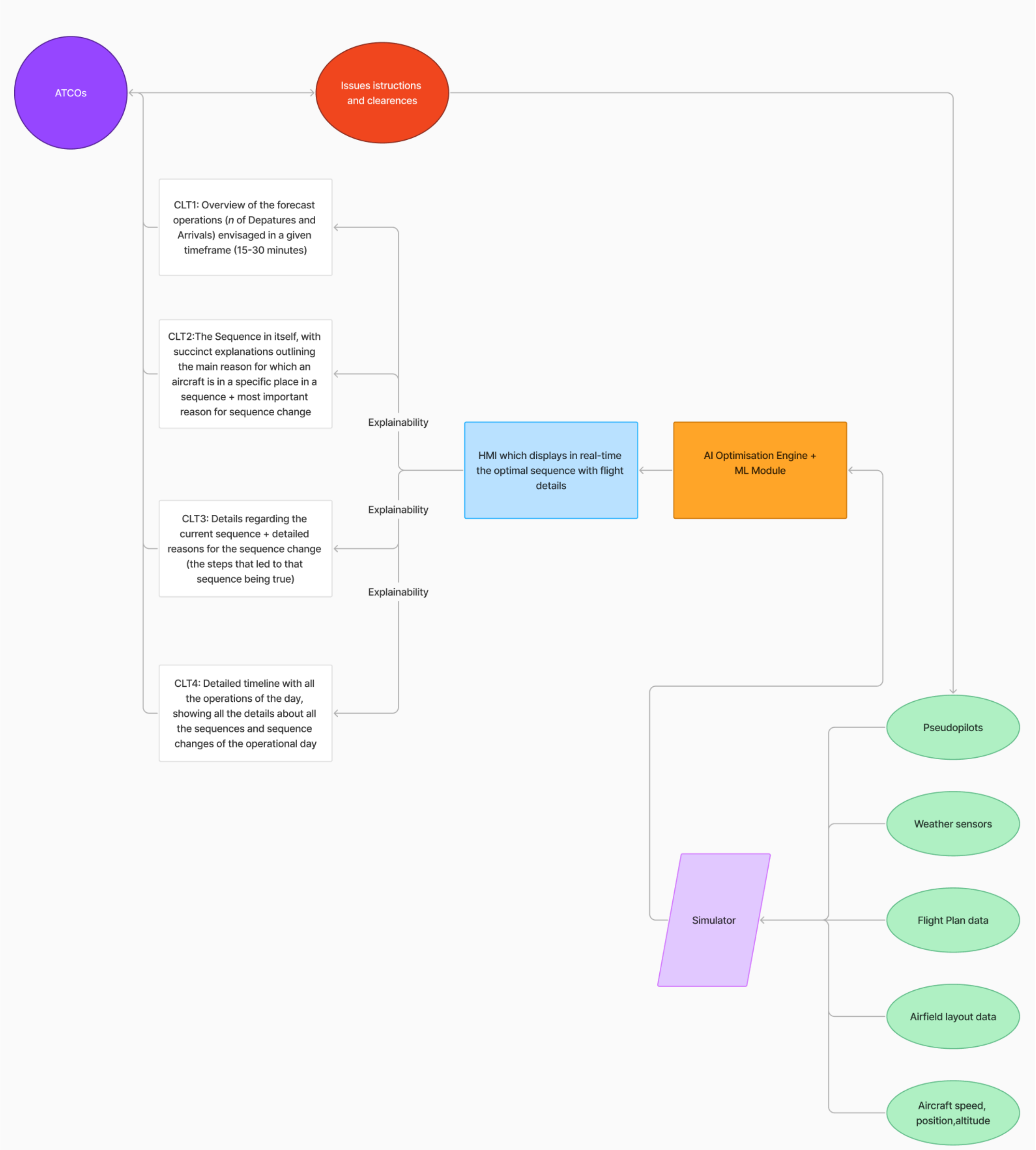


Figure 8: Communication model implemented in the simulator for use case 4.

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Data	**Data type**
Static airport information	Runway and taxiway coordinate, stands position and restrictions, etc.
Rules of the air	Preset rules regarding minimum take-off separation between aircraft, runway occupation, etc.
Flight information per aircraft	Arrival/departure, origin, destination, aircraft type, aircraft model, wake turbulence, assigned parking stand, flight rules, squawk, callsign, etc.
Timestamp information per flight	Position, altitude and events (clearances and instructions issued by ATCOs).

Table 11: An example of data and data types.

The current model is based on **visual** communication as the primary modality via the HMI, where textual explanations and sequence information are displayed. For this information to be generated, there's a complex process that comprises several inputs and outputs.

The inputs for the Intelligent Sequence Assistant (ISA) model primarily come from two sources: the air traffic controllers' instructions to aircraft and all the data fed by the sensors. The controllers' instructions are vital as they issue specific commands to the aircraft such as clearances for takeoffs and landings. These instructions are captured and recorded in real-time by the ISA system, allowing the flight sequences to reflect the most recent operational decisions and immediate needs of the control tower. This ability to incorporate human decisions into the automated process is essential for maintaining flexibility and adaptability in a dynamic operational environment.

On the other hand, sensor data (simulator) provides an objective and continuous basis on which the ISA system can operate. This data is integrated and validated by the ISA system to ensure its accuracy and relevance, forming a real-time dataset that feeds into the optimisation algorithms. The combination of these two types of inputs – controllers' instructions and sensor data – enables the ISA system to calculate and adjust optimal arrival and departure sequences for aircraft, thereby enhancing the efficiency and safety of air traffic at single-runway airports.

The optimisation module includes several internal data flows and submodules: ML modules which provide the ETA, optimisation model which provides the optimal flight sequence, explanation generation submodule.

The core data processing module receives:

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

- Static airport information: runway and stand coordinates
- The active runway
- Time separation between consecutive flights (there is a predefined value for this, but it is also adjustable by the user via a dedicated property)
- Per flight information:
    - arrival/departure/overflight indication
    - aircraft type
    - aircraft model
    - wake turbulence
    - assigned parking stand
    - flight rules
    - emergency flight indication
    - flight type (operational or other)
    - EOBT or CTOT for departures
    - callsign
- Per flight & per timestamp information:
    - Events (e.g., clearances, landing & takeoff confirmation, status changes): For each event, the timestamp, description and value are provided.
- Positions (X, Y, Z), track and true air speed for each timestamp according to the defined frequency

And outputs:

- The optimal aircraft sequence
- The explanations for the sequence and for the sequence changes

The intermediate outputs include:

- Calculated taxi times
- Callsigns that should be considered in the sequence optimisation (e.g. departing aircraft are considered after they reach a certain status)
- Callsigns whose ETA should be calculated

The ML modules for ETA get as input:

- Active runway
- Per timestamp & per callsign
    - Aircraft positions (x,y,z)
    - Aircraft track
    - True air speed
    - Indication of whether the aircraft is on the ground

The module’s output is the estimated seconds until landing for each provided callsign (arriving flight).

The sequence calculation module provides the proposed flight sequence and gets the following as input:

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

- Calculated taxi times per callsign. These are now extracted from the core module based on statistics (In the future, the usage of an ML model might be examined).
- Time separation between consecutive flights is computed per aircraft pair according to the provided rules. This is also computed by the core module and provided to the optimisation algorithm as input.
- Per call sign information: arrival/departure/overflight, flight rules, emergency indication, flight type (operational or other)
- For departures: EOBT or CTOT
- For arrivals: ETA from the ML submodule

The output of this module is the rank (sequence number) assigned to each callsign, together with the calculated time for arrival or EOBT/CTOT.

The explanation generation module takes the following as input:

- The sequence calculated by the optimisation submodule at the current step & at the previous step
- Per call sign information: whether it is an arrival/departure, its flight rules, whether it is an emergency or not, and its flight type (operational or other)
- ETA or EOBT/CTOT for arrivals or departures, respectively. The value of the current step (timestamp) and the previous N ones are used.

The outputs:

- The explanation for the aircraft sequence
- The explanation for the sequence change if the sequence in this step differs from the one in the previous step. This is provided per callsign for all callsigns whose order in the sequence changed between the two steps.

4.4. Component integration and mapping to CLTs

The components mentioned in the previous sections are integrated into a unified system that provides the described functionality in an end-to-end manner. Some parts of the information flow are synchronous and others asynchronous, like what is expected in real-life scenarios. Data from sensors (weather data, aircraft positions, etc.) continuously flows into the system using a message queue. Different processes of the AI-enabled data processing components (ETA calculation, sequence calculation, explanation generation) can be triggered according to the received messages, coordinated by the core data processing module. At the same time, even if no data arrives, the sequence calculation submodule will recompute the sequence every second. The following diagrams provide the basic information flow, with dashed lines presenting asynchronous communication.

The diagram in Figure 9 provides a high-level view of the communication model that supports the provision of the CLT1 functionality, i.e. the expected arrivals and

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

departures within the next minutes (number of minutes can be adjusted by the ATCO). Since CLT 1 relies on schedule (EOBT/CTOT) data for departures and ETA for arrivals, not all modules of the AI system participate and are thus not shown.

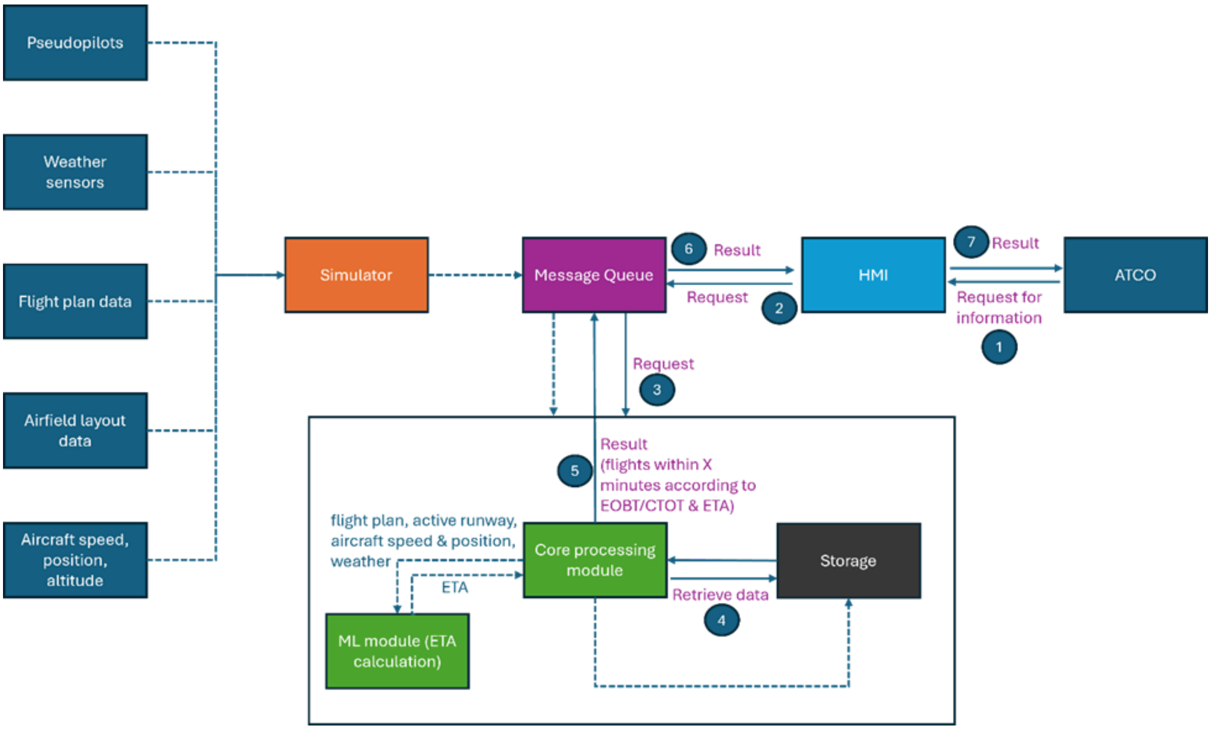


Figure 9: High-level communication for CLT 1.

It should be noted that ETA of all active arrivals that are within 20 minutes from landing is constantly updated every second (& corresponding HMI information per flight is also updated), independently of whether the ATCO explicitly requests to see the CLT1 overview. When the request comes, messages are exchanged as shown to retrieve and provide the result.

For all 3 other CLTs (CLT2-4), the information flow is essentially the same and involves all components, bidirectional communication between many of them, synchronous and asynchronous data retrieval and processing. The core processing module acts as the coordinator for most processes, ensuring that calculations are timely performed and in the correct order, while the system keeps ingesting real-time information and processes are adjusted to always reflect the most up to date data (raw and computed) and ensure that these are always made available to the ATCO as needed (upon request or as part of the continuous updates). Figure 10 provides a high-level view of this complex communication model that allows the system to offer CLT2-4 functionalities

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

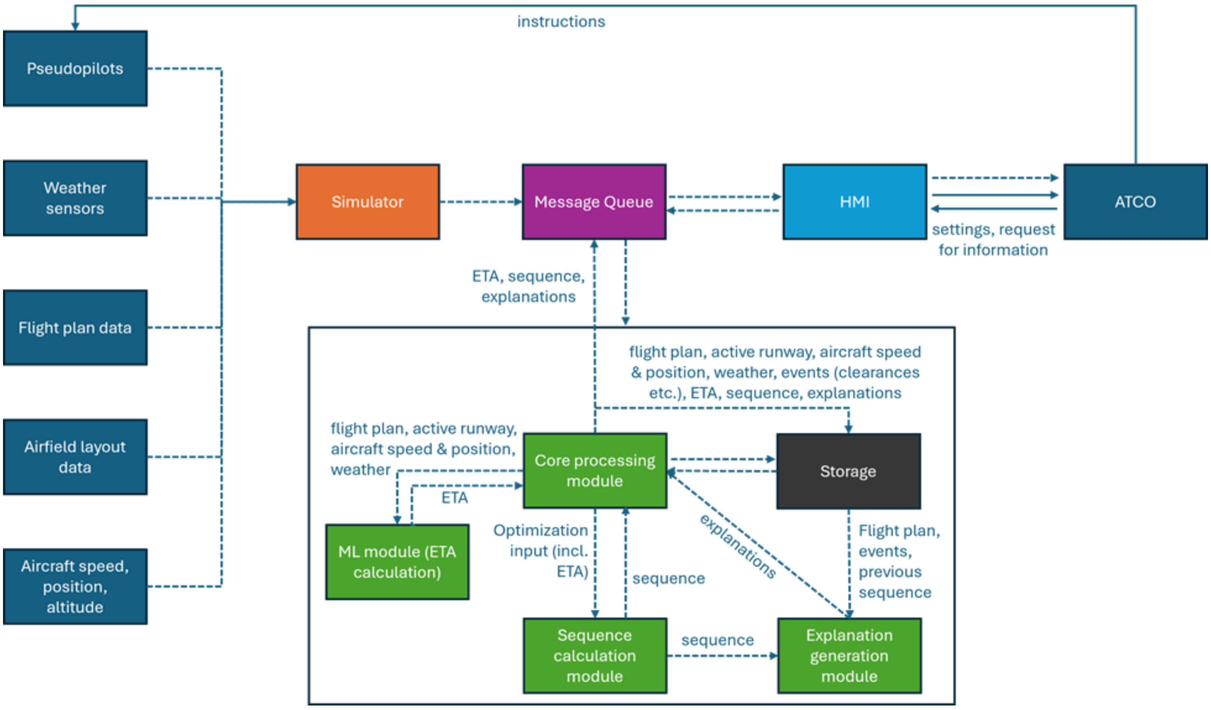


Figure 10: High-level communication to support CLT2-4.

The interactions shown in Figure 10 are a simplified version of the complete communication model, which encompasses various flows. To offer a more detailed view, the diagram in Figure 11 shows the information flow for one of the many supported actions, scenarios, and statuses, specifically what happened after the ATCO clears a departing aircraft for pushback. It should be noted that all data sources remain active, and information keeps flowing into the system asynchronously, therefore the dashed lines are not removed, since this is a real-life system that is continuously updated, i.e. we cannot expect that the system remains static until the clearance order is processed.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

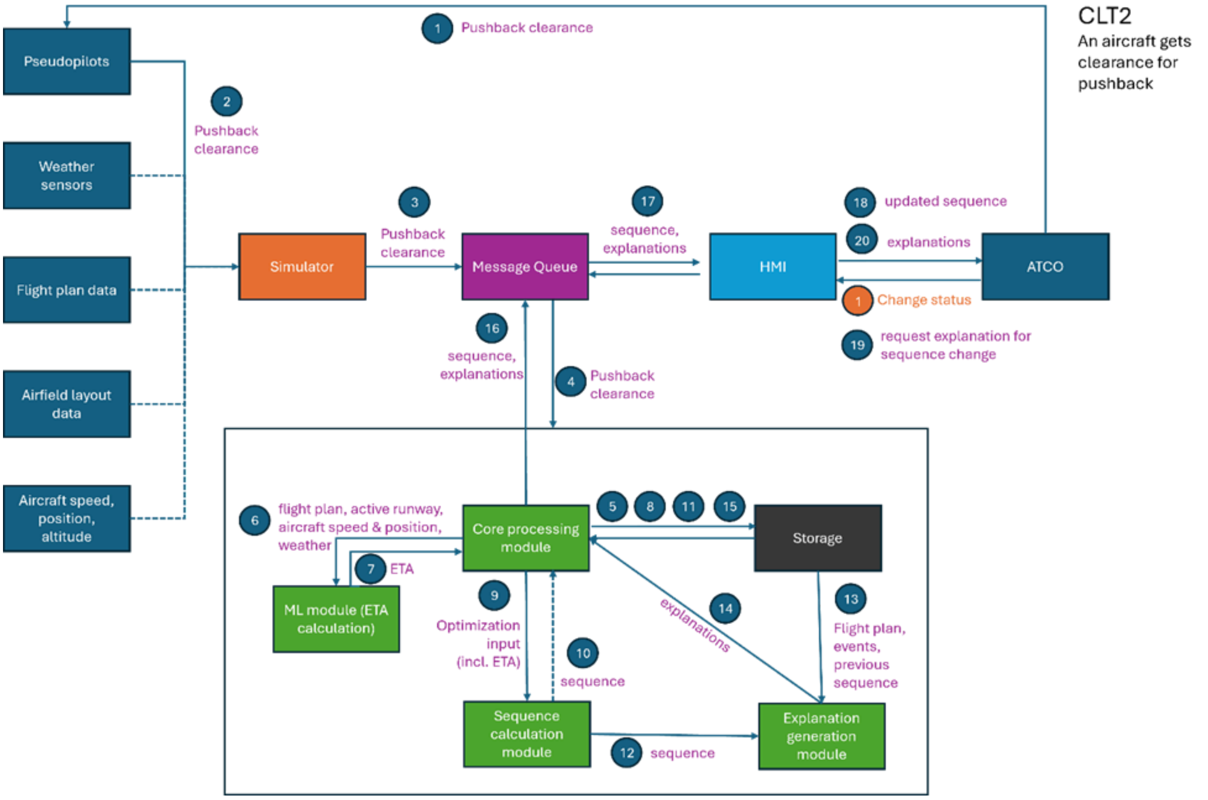


Figure 11: CLT2 subcase - Communication following pushback clearance action

Based on Figure 11, there are two entry points (number 1 circles). This is because the ATCO actions are in a way duplicated: the actual clearance is issued to the pseudo pilot, and this is what is ingested in the system and triggers the sequence computation. However, ATCOs also independently change the flight status in HMI so that the screen reflects the real-world situation. This is not a limitation imposed by the system, but an actual ATCO requirement. ATCOs interact with the system to view the information that is provided, to request additional information (in the form of explanations or expected load overview), to update the aircraft statuses or otherwise adjust what is shown to them (e.g. change sequence length or disable ISA for a period) but do not explicitly provide feedback to the system. Instead, feedback is indirectly received by the system through the ATCOs actions and non-actions through which it can be inferred whether the ATCO wants to follow the proposed system or not. The system will adjust its calculations to ensure that the ATCOs decisions are taken into consideration. At the same time, at a later stage, the stored information can be used to check in which situations the ATCO chose a different sequence and if needed, adjust future versions of the system.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

4.5. Validation 1

During validation 1, the HMI concept and CLT levels were validated by having the users watch a video of the mock-up, simulating the actual behaviour of ISA. According to the feedback the following adjustments were made for each level:

CLT Level	Before Val 1	After Val 1 (with feedback integrated)
1	The number of safety events, departures and arrivals.	Only departures and arrivals (Color for easy-reading)
2	All the aircrafts involved in the sequence. The hover explanation was a phrase about the main reason for the sequence change.	Shows 3 aircrafts (the next ones to use the RWY). The explanation was made shorter.
3	Importance to the sequence displayed by percentage numbers.	Only the main data feature involved in the sequence change, and the steps that led to the current sequence
4	The timeline representation of all the operations.	unchanged
5	-	Scrapped.
6	-	Scrapped.

Table 12: CLT update and change after validation.

4.6. Validation 2

Regarding XAI, in VAL2 we dedicated a specific section of the semi-structured interviews conducted during the exercise debriefings to investigating the XAI components. We developed a set of questions mapped to the EASA-like requirements defined in D4.1, aiming to understand how ATCOs perceived these components and whether they leveraged them during the exercises. The specific questions used are included in the table below:

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

EASA-like requirement (D4.1)	**Question**
EXP-10: ISA must be able to generate explanations related to sequence generation (for monitoring), and ad-hoc explanations for sequence changes	• Q5: Can you describe how well ISA's explanations matched your expectations as to why a specific suggestion was made? • Q6: To what extent did you trust ISA’s recommendations? What influenced your level of trust? • Q7: In what ways did Explanations help you in your decision-making process?
EXP-11: ISA HMI must show explanations related to sequence generation and sequence changes	• Q8: Can you walk me through how you interpreted ISA's recommendations and the explanations provided?
EXP-12: ISA must be able to show, for each sequence change, different levels of explainability with a progressive level of detail that is keyed to the expected decision / action	• Q9: Were the level of details provided useful in the different situations you faced?
EXP-13: ISA HMI must provide a means for user to discover progressive levels of detail details about any provided explanation	• Q10: Were the level of details provided useful in the different situations you faced?
EXP-15: Explanations about sequence changes must be available to the user minimum delay, and permit progressive levels of detail keyed to user needs.	• Q11: In terms of timing (i.e.: when the explanations are provided), were the explanations presented appropriately? • Q12: Was the timing of the blinking appropriate?
EXP-16: The user must be able to access ISA explanations about sequence changes, via progressive disclosure interaction, as desired by the user.	• Q13: In what cases would you need to delve deeper into the details of the explanation?

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

EXP-17: ISA-generated sequences must optimize operational priorities (by default, throughput shall be optimized)	• Q14: What do you think are the main parameters that influence ISA's explanations?
EXP-19: ISA must alert user to any potentially unsafe ISA-recommended sequences (which can be caused by outdated recommendation, or off-nominal flight trajectories).	• Q15: What do you think is the reason behind the blinking on the interface?

Table 13: EASA-like Requirements for UC4 - how they were explored during validation

Based on the results of VAL1 and VAL2, the main findings for UC4 regarding XAI can be summarised as follows:

Explanations were considered valuable in supporting user interaction with the system, but their usefulness depended heavily on the overall system performance. In VAL2, the prototype worked sufficiently well, which made the presence of explanations meaningful and relevant. Had the system failed to perform, explanations alone would not have compensated or supported user trust.

The explanation model based on the CLT framework was positively received. Participants consistently used CLT2 explanations, which provided concise, text-based justifications for AI outputs, particularly during sequencing tasks such as checking aircraft ETA times. Embedding these explanations within a mouse-hover interaction on the electronic strip interface made them easily accessible without interrupting the workflow. This level of explanation struck an effective balance between informativeness and operational efficiency. Other levels were used more selectively: CLT1 was relevant at the beginning of operations, CLT3 during quieter moments, and CLT4 mainly after operations. While these higher levels were accessed less frequently, participants recognised their value for training or debriefing. Overall, the layered structure proved effective in helping users navigate information without overwhelming or cluttering the interface, with CLT2 accounting for most interactions.

VAL2 confirmed that the design was well implemented, receiving positive feedback both through user comments and observed behaviour. The consistent use of CLT2, especially via the mouse-hover feature, reinforced its practical value and usability. Feedback also suggested that even more minimal formats, such as icon-based representations of CLT2, could be explored in future versions.

In conclusion, the UC4 findings highlight that explainability is only valuable insofar as it does not overwhelm the user and is delivered at the right time, with the appropriate level of detail. The key takeaway is that, when integrating XAI into safety-critical systems like ISA, balance is essential. A minimal, user-centred approach is often more

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

effective than comprehensive but intrusive explanations. Sometimes, no explanation is needed and forcing it can be counterproductive. Designers must first understand what users need and when, and only then define the most unobtrusive and effective ways to integrate explainability into the HMI.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

5. Use case 5: Airport safety management

5.1. Context

The Airport Safety Watch (ASW) dashboard serves as the main interaction point between the system and the London Luton Airport (LLA) safety department personnel. It is specifically designed to effectively and understandably convey information from incident reports to the users. While not strictly an eXplainable AI (XAI) dashboard in the traditional sense of AI model interpretability, its interface is intentionally designed to enable users to grasp displayed data and explore incidents comprehensively and efficiently. The addition of a Large Language Model (LLM) component further enhances ASW's XAI capabilities by providing information in natural language.

5.2. Construal levels

The Airport Safety Watch (ASW), as detailed in D5.1, depends significantly on analysing safety and operational data from airport operators, airlines, and handling services.

Its primary objectives are twofold: first, to analyse recurring incident types such as pushback errors and incorrect taxiway selection to develop solutions for their reduction; and second, to predict the operational risk on specific days based on identified risk factors.

The latter part did not yield meaningful outcomes due to insufficient data to train accurate AI forecasting algorithms. However, the chosen approach allows for future re-runs of the AI modelling and algorithm training phases. This will enable an evaluation of whether data collected during project operation can form a basis for meaningful forecasts.

The CLT table for UC5 is the following:

CLT Level	Applicability	Description
CLT 1	Airside Users (Ground Handlers, Flight Crew, ATC)	Highlighted risks from the weekly analysis, e.g. ‘heatmaps’ of hotspots on the taxiway system, weather issues, Pushback error potential given ongoing maintenance work on the apron, etc.
CLT 2	Airside Users (as for CLT 1) plus Base Captains.	CLT 1 + : The key triggering factors and conditions feeding into the current highlighted risks (heatmaps etc.).

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

CLT 3	Operation/ Stack partners (supervisors and middle management)	CLT 2 + : Awareness of the incidents and analyses underpinning the operational safety intelligence given to airside users.
CLT 4	Operation/ Stack partners, Operational and safety managers	In-depth analysis of key incident types, such as taxiway selection errors, analysed using the 'causal tree' breakdown functionality in the ASW dashboard, along with various statistical analyses.
CLT 5	Operation/ Airside operational safety leadership	The full analysis of the risk data will be provided to the partners if they wish, and they can have access to the Dashboard for verification and further exploration (e.g. to compare with their own internal analysis systems).
CLT 6	Safety Analysts, Data Scientists	Full access to the data and how it has been clustered etc., including data 'ignored', down to the scripts used by the Dashboard algorithms.

Table 14: CLT levels for Use Case 5

The table outlines different Communication Level Targets for operational risk information distribution. CLT 1 is focused on highlighting risks to airside users with information like heatmaps and weather issues, and the final one, CLT 6, is offering full data access and algorithmic scripts to safety analysts and data scientists. Each level builds upon the previous, increasing the depth and specificity of risk data. CLT 2 adds trigger factors and conditions to CLT 1's information, while CLT 3 makes operational and stack partners aware of the underlying incident analysis. CLT 4 provides in-depth analysis of key incident types, while CLT 5 grants full data access and verification.

We do not have additional elements to propose for the CLT framework; however, throughout its implementation, we encountered a key limitation: despite having a numerically significant dataset, the actual number of incidents was relatively low, which restricted the depth of analysis we could perform. This scarcity of events, while positive from a safety perspective, posed challenges in extracting statistically robust insights.
Nonetheless, the project allowed us to develop a user-oriented system that enables clear visualisation and analysis of operational risk information. One of the most tangible outcomes was the identification of a safety issue on one of the airport runways, which led to a change in signage, an improvement that directly enhanced operational safety. This result alone confirms the value of the CLT approach.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

We also explored the integration of external data sources, such as weather services, to enrich the information provided. However, this did not yield significant added value. In practice, pilots already adjust their behaviour appropriately in low-visibility conditions, which limits the operational impact of such data within the CLT framework.
Overall, we are satisfied with the outcomes achieved and believe the CLT structure has proven effective in supporting both awareness and action in operational risk management.

5.3. Communication model

The flight and incident data coming from the UC5, including pushback, incorrect taxi routing and holding point busts, are collected and visualised on a dashboard which we named *Airport Safety Watch* (ASW). The ASW is composed of two visualisations:

- The Flight Intelligence, which focuses on aggregated airport traffic data linking flight activity and safety incidents to analyse trends and identify patterns indicating increased risks;
- The Exploratory Data Analytics, which focuses on analysing safety incidents at the airport, identifying trends, and allowing detailed investigations.

To achieve the final visualisation of the ASW a processing data pipeline (Figure 12) was set up to correctly clean, preprocess, store and analyse the UC5 flight and incident data. This pipeline allows for a flexible integration with the data source that London Luton Airport (LLA) can provide and outputs a refined data frame to be used for the Flight Intelligence and the Exploratory Data Analytics and shown in the ASW.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

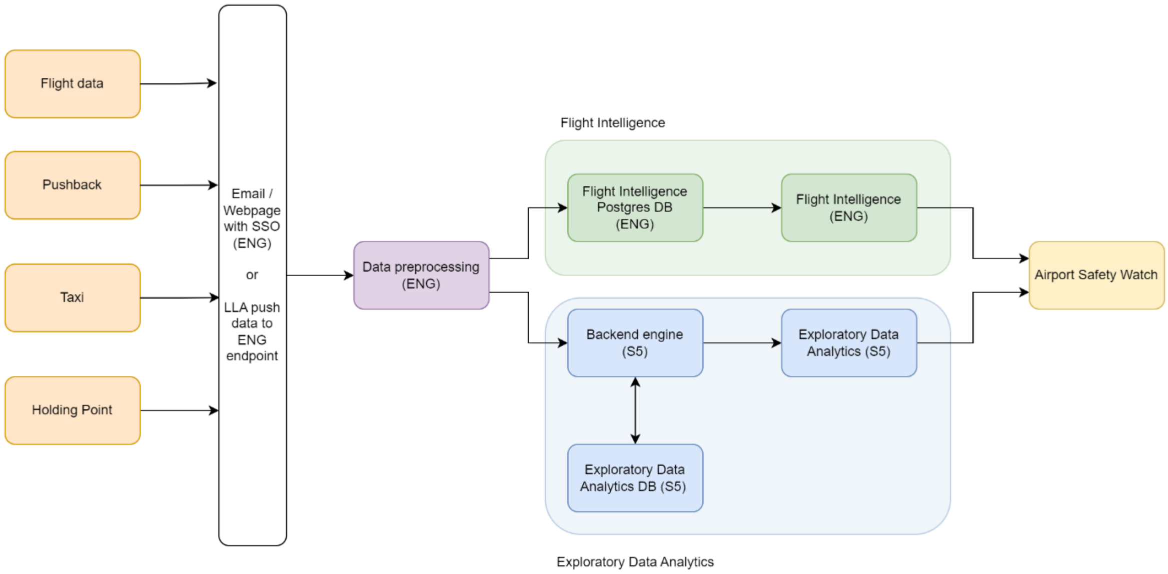


Figure 12: ASW model

The processes are specific to the use cases and involve the participation of IA and the human. For UC5, the following functionalities can be captured as communication models:

- Historical view of the data acquired for LLA,
- Aggregate airport traffic data,
- Link flight activity to safety incidents,
- Analyse trends in safety incidents,
- Identify patterns indicating increased risks,
- Allow detailed investigation of safety incidents,
- Explore trends with fine granularity.

The AWS dashboard presents visualised textual and graphical representations of analysed airport data to users.

User inputs within the dashboard primarily involve selections across several key dimensions: the specific types of incidents they wish to examine, the particular time frame of interest for their analysis, and choices regarding the types of diagrams and the specific data dimensions to be displayed visually.

A detailed examination of the historical data pertaining to LLA encompasses an extensive repository of past information concerning flight operations, the volume of passenger traffic, and reported safety incidents. This historical data serves as a foundational element for establishing performance benchmarks, discerning long-term trends in airport operations and safety, and evaluating the efficacy of previously implemented safety protocols and interventions. By meticulously analysing this historical information, LLA can derive critical insights into the ways in which various

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

operational and environmental variables have historically influenced safety outcomes. This understanding empowers the airport authorities to make more informed and data-driven decisions aimed at proactively enhancing future safety protocols and resource allocation strategies.

The process of aggregating airport traffic data involves the systematic compilation and consolidation of information sourced from a diverse range of operational systems and reporting mechanisms. This aggregation aims to create a unified and holistic view of overall airport operations. The data encompassed within this aggregation includes, but is not limited to, the total number of flight movements (arrivals and departures), detailed passenger counts (enplanements and deplanements), and other pertinent operational metrics such as cargo volume and aircraft type distribution. This aggregated data provides a comprehensive snapshot of the airport's activity levels, enabling analysts and decision-makers to understand overarching traffic patterns, identify periods of peak operational demand, and assess the impact of external factors such as adverse weather conditions, regulatory changes, or significant local events on airport throughput. This consolidated perspective is indispensable for effective airport management, strategic resource planning, and the optimisation of operational efficiency.

Establishing a clear linkage between flight activity data and recorded safety incidents represents a crucial analytical step towards comprehensive understanding the complex interplay between routine operational practices and safety outcomes. This process involves systematically correlating detailed flight schedules, precise aircraft movement records, and other relevant operational data (such as runway utilisation, taxiing patterns, and gate assignments) with the specific details of logged safety incidents. By identifying these correlations, analysts can uncover potential causal factors and pinpoint specific operational areas or conditions that may be associated with a higher propensity for safety-related events. This refined understanding facilitates the identification of specific flights, particular times of day, or unique operational conditions that might present elevated risks, thereby enabling the implementation of targeted interventions, the refinement of operational procedures, and ultimately, significant improvements in overall safety protocols and risk mitigation strategies.

Analysing trends in safety incidents involves a systematic examination of the frequency, severity, and diverse types of reported incidents over extended periods. This longitudinal analysis is essential for identifying recurring patterns, such as a statistically significant increase in specific categories of incidents (e.g., ground handling accidents, runway incursions) or a notable rise in the overall incident rate during seasonal periods or under specific operating conditions. By diligently tracking and interpreting these evolving trends, LLA can proactively anticipate and address emerging safety challenges, strategically allocate safety-related resources with greater efficiency, and implement targeted preventive measures designed to effectively

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

mitigate identified risks and enhance the overall safety posture of the airport. Trend analysis is therefore a vital component of a continuous improvement framework for airport safety management.

The process of identifying underlying patterns that may indicate increased levels of risk involves the application of advanced analytical techniques to detect anomalies, recurring issues, and subtle correlations within the comprehensive safety data. These identified patterns can serve as early indicators of latent systemic problems or emerging risks that might not be readily apparent from the examination of individual, isolated incidents. By leveraging sophisticated analytical methodologies, including machine learning algorithms and data mining techniques, LLA can effectively uncover nuanced indicators of heightened risk, such as a recurring pattern of minor maintenance discrepancies on a specific aircraft type or a statistically significant correlation between operational procedures and a specific category of near-miss events. The ability to recognise and interpret these subtle patterns enables proactive and pre-emptive interventions to enhance safety, prevent potential future incidents, and foster a more resilient operational environment.

Facilitating the detailed investigation of safety incidents necessitates the implementation of a robust system capable of enabling in-depth examination of specific cases and their comprehensive analysis. This requires seamless access to granular levels of data contained within the original incident reports, including detailed narratives, witness statements, environmental conditions, and equipment status. These thorough investigations are critical for uncovering the fundamental root causes of incidents, identifying contributing factors that may have exacerbated the event, and revealing any potential lapses or deficiencies in existing safety procedures. A deep and comprehensive understanding derived from these detailed investigations is essential for the development of effective and targeted corrective actions, the implementation of preventative measures designed to address the identified root causes, and ultimately, for minimising the likelihood of similar incidents occurring in the future.

Exploring trends with a high degree of granularity entails the analysis of data at a very detailed and disaggregated level to uncover valuable insights and subtle patterns that might be obscured or missed in broader, more aggregated analyses. This involves examining data within specific, narrow timeframes (e.g., hourly or even shorter intervals), scrutinising the operational characteristics of individual flights, or focusing on very specific and localised operational conditions (e.g., aircraft movements on a particular taxiway segment under specific weather conditions). This fine-grained level of analysis allows for the identification of micro-trends, highly localised issues, and subtle variations in safety performance that might not be apparent at a higher level of aggregation. This detailed understanding is crucial for tailoring safety interventions to very specific contexts, optimising the effectiveness of safety measures, and ensuring that risk mitigation strategies are precisely targeted and highly relevant to the specific operational environment in which they are applied.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Finally, the system provides users with the capability to interact with the AWS environment through natural language queries. In this mode of interaction, users can input their questions and analytical requests in a conversational and intuitive manner, using everyday language. The system then processes these natural language queries by leveraging a pre-trained Large Language Model (LLM). This LLM has been trained on the body of knowledge accumulated from the amount of data ingested into the system. Based on its understanding of the user's query and the available knowledge, the system is able to generate relevant and informative responses, effectively answering the user's questions and providing insights derived directly from the underlying data. This natural language interface enhances the accessibility and usability of the system, allowing a wider range of users to interact with and extract valuable information from the analysed airport data without requiring specialised technical skills in data querying or analysis.

5.4. Validation 1

For VAL1, a questionnaire was developed, as well as presenting CLTs to the Stack Partners at a Stack meeting, to see what they desired. The results of these and subsequent discussions have led to the strata as shown in Table 10 above. These will be tested in VAL2.
The first usage of the ASW insights, generated by a weekly update of the Dashboard to be implemented in September 2024, is a briefing by the LLA Airside Safety lead on HAIKU to Airside Ops personnel who are dealing with the full range of airside users every day. These personnel carry out what are known as ‘Points of Engagement’, where they approach airside operational staff to give them the latest safety intelligence related to their tasks. Thus, for example, they may warn pilots - particularly those less familiar with the geographical layout of taxiways at Luton Airport (LTN) - about potential hotspots, via heat-maps generated by ASW. Such advice will be CLT1 (hazards) plus CLT2 (principal causes) if asked or if they feel it is germane to the warning they are giving.

The second usage (CLT3) is to advise the Safety Stack partners of the principal risks according to the ongoing ASW analysis, to see how useful this is to the Stack partners. Currently at Stack meetings, incident information is presented via static graphs in PowerPoint, followed by Q&A. This is effective but ‘Old School’, so the idea is to have a more dynamic presentation where Partners can ask questions and see immediately how their questions change the data.

The third usage is to carry out a ‘deep dive’ on a key incident category. The first deep dive using the ASW Dashboard will occur in October 2024, with pilots and ATC

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

personnel present, using the functionalities of ASW to 'drill down' into potential causal factors.

VAL2 will therefore evaluate the effectiveness of these three usages of the Dashboard.

5.5. Validation 2

During VAL2 the explainability of the *ASW* was tested. The set of explainability requirements selected for VAL 2 are shown in the following Table:

EASA-like EXP requirements for UC5
EXP-13: Define level of abstraction of explanations according to task, situation, trust, expertise of users
EXP-16: Enable explanation and details upon user request
EXP-18: Provide instructions/training to handle indications of input/output monitoring

Table 15: EASA-like EXP requirements for UC5

VAL2 allowed for further improvements to the UC5 Explainability strategy and Communication model. In the following chapters 6.2 and 6.3 the final versions of the Construal levels and Communication model are presented, remarking the changes made after VAL2 (compared to the previous versions presented in D5.2 first release). The main conclusions of UC5 on XAI are presented in chapter 6.4.
It needs to be mentioned that UC5 is not approaching VAL2 as an experimental setup, but as a process of TRL progression. The VAL2 HAT requirements, activities and success measures for UC5 are given in the text and tables already described in D6.3 'Updated validation strategy and plan' (ref. See table 78).

According to VAL1 and VAL2 results, the UC5 main findings concerning XAI can be summarised as follows:

Within the framework of the use case, the system's ability to effectively meet the needs of end-users was fundamentally dependent upon a cyclical design methodology. This approach prioritised the creation of easily understandable user interfaces and the integration of user-centric explainability mechanisms. This orientation represents a departure from a more traditional, algorithm-focused perspective within the field of XAI. Such algorithm-centric views often concentrate

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

primarily on deciphering the internal logic and outputs of intricate machine learning models.

In contrast, UC5 places a significant emphasis on explainability not as an inherent property of the algorithm itself, but rather as a tangible attribute experienced directly by the user. This user-facing explainability is achieved through the deliberate and effective deployment of visualisations and interactive dashboards. These visual elements serve as the primary channels through which insights, derived from the detailed analysis of numerous post-incident de-briefing reports concerning safety incidents within the London Luton Airport operational environment, are communicated to the intended users. The central aim is not to furnish a highly detailed, step-by-step account of the algorithmic decision-making processes. Instead, the system focuses on abstracting the most pertinent information and presenting it in a readily digestible and immediately actionable format for the target audience, which comprises airport safety personnel. This abstraction ensures that the information provided is directly relevant to their operational responsibilities and cognitive processing capabilities.

The demonstrable success of UC5 can be directly attributed to an ongoing and dynamic exchange, coupled with a strong collaborative partnership, between the technical development team responsible for building the system and the aviation operational staff who are the ultimate end-users. This interdisciplinary approach guarantees that the explainability features and functionalities embedded within the system are closely aligned with the practical demands and established cognitive frameworks of the individuals who will be interacting with it daily. As a direct consequence of this user-centred design philosophy, the system delivers insights that are not only comprehensible but also directly actionable, thereby providing concrete support to airport safety personnel in the execution of their routine operational duties. This outcome powerfully underscores a particular paradigm of XAI. In this paradigm, the central focus shifts away from the intrinsic interpretability of the underlying model's mechanics and towards the extrinsic goal of fostering genuine user understanding. Furthermore, it highlights the critical role of well-designed user interfaces and effective information presentation in facilitating informed decision-making in real-world operational contexts. The iterative feedback loops between developers and users ensure continuous refinement and optimisation of the explainability features, further enhancing the system's utility and user acceptance.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

6. Use case 6: Airport virus spread prevention

6.1. Context

The name of the Intelligent Assistant of UC6 is COVID-19 AID (COVAID). COVAID leverages two applications to accomplish two goals. The primary goal and expectation of COVAID is to route passengers in the airport common places to places that are not overcrowded without compromising their preferences. It is essentially a recommendation application operating on Android phones. The secondary goal is to inform health and safety officers regarding the air quality of the airport premises. In both applications, respective sensors (cameras, air quality sensors) are deployed that send real-time information on the readings.

In terms of XAI, in UC6, COVAID provides explanations for the routing sequence suggested to the passenger, which is detailed in D4.2 and D4.5. This operation takes as input the preferences of the passenger, outputs the likelihood of infection and the routing sequence as well as the CLT levels 2-4 as automated messages to the chat service with weighting factor and sensor data.

6.2. Construal levels

The final CLT levels utilised in COVAID are 1-4, with the timely manner to be satisfied at the Android application. The CLT1 is output in the Notifications tab, while the remaining 3 levels are automated messages in the chat service of the application. The details of the CLT levels employed are given in the following table.

The CLT table for UC6 is the following:

CLT Level	Applicability	Description	Changed after VAL2
CLT 1	During operation	Infection likelihood and routing sequence given in the Notification tab	No
CLT 2	During operation	Initial automated message by the chat at a predefined time of the journey to initiate further explanations	Yes The message has been altered to provide initial explanation to the passenger

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

CLT 3	During operation	The weighting factor values are given to put the passenger in awareness regarding the AI process	Yes, the weighting factor values have been set according to the predefined time frame with sensor data integrated
CLT 4	During operation	The sensor values for each common place selected are given to inform the passenger of the persons in, queuing and going to each common place	Yes, finalised version of the level has been provided
CLT 5	Not used	Not used	Yes, discarded.
CLT 6	Not used	Not used	Not used.

Table 16: CLT Levels for Use Case 6

The primary lessons learnt from the XAI CLT levels are attributed to the implementation of COVAID. The integration of the sensors and the passenger preferences is a challenging task. The dynamic nature of COVAID changes the CLT levels according to the number of people in the system. The CLT levels themselves produced a way the passengers to become part of the AI engine so that they begin to trust the system. Certainly, the more the passengers use it and verify the sensor values from the CLT4 the more they will get used to the idea of COVAID. We do not believe that we should overwhelm the passengers with more information, even though a more custom approach and a requirement by the passenger may provide a more personalised CLT explainability.

6.3. Communication model

The Intelligent Assistant (IA) of the COVAID use case was developed to inform passengers about the likelihood of COVID-19 infection at the airport and to guide them through their visits to the airport's common areas. Beyond providing infection likelihood information, the IA also includes a chatbot that engages passengers in conversations about their journey to the airport both before the flight and during the routing process with the respective CLT explanations. Moreover, a second system exists that provides information and explainability plots with respect to air quality in the airport common places. In Figure 13, we can see the primary COVAID routing engine communication model. In Figure 14, we can see the air quality system communication model.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

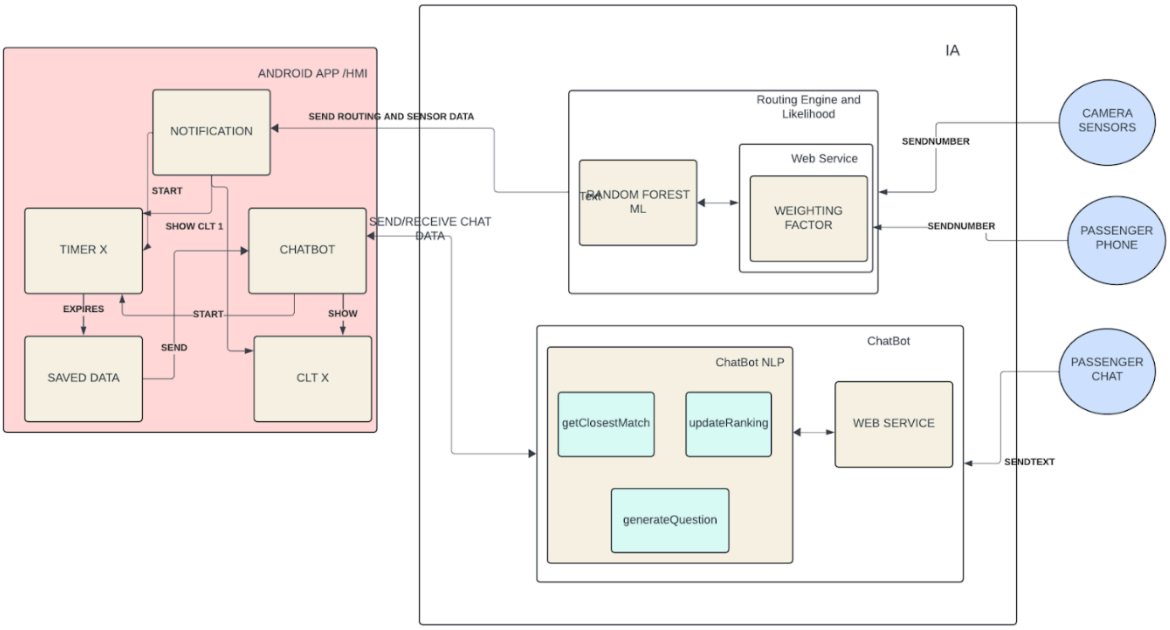


Figure 13: Top level of communication model of the COVAID routing application

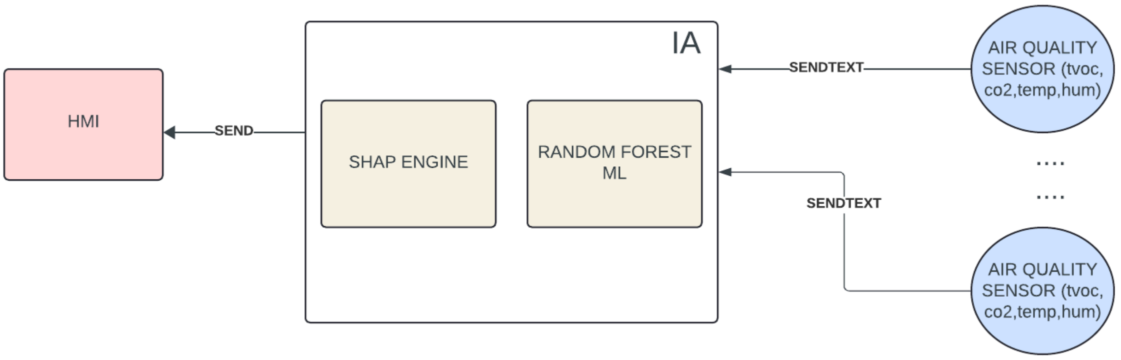


Figure 14: Communication model of air quality system

For the routing application, the primary changes made after the initiation of VAL 2 are as follows: CLT1 has not been changed, and it gives the likelihood of the COVID-19 infection and provides the routing sequence as a future event to be followed. The primary difference is that the entire sensor system is operational at the airport. CLT2 provides a specific introductory explanation as an automated message in the chat when the first timer fired as given in D4.5. With CLT3, it provides the weighting factor sequence which brings the passenger to an acquaintance with the routing process. CLT4 provides the current sensor data which were responsible for the routing decision and allows the passenger to have knowledge about the occupancy, queue and people going towards that common place in the sequence of the routing decision. All CLT

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

levels are provided upon the firing of specific software timers in the Android application. In terms of the air quality application the explainability plots, which are based on SHAP have not been changed.

In terms of processes, we will provide the air quality part of the communication model which has not been changed after the initiation of VAL2. The data flow is given in Figure 15.

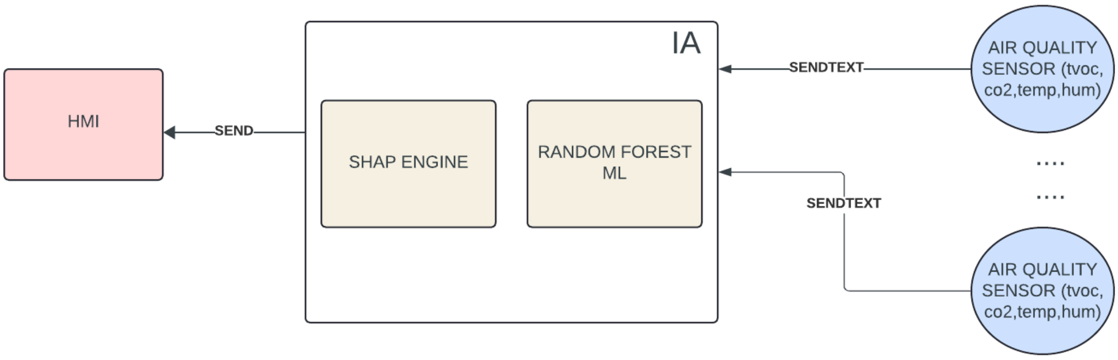


Figure 15: The routing process model.

The figure illustrates the data flow process for indoor air quality monitoring by the health and safety officers, where sensor data is transmitted to a cloud service for further processing and analysis. Initially, the collected data undergoes statistical evaluation, with key indices displayed on the screen for monitoring. Following this, the entire dataset, categorised by feature, is visualised, allowing for a deeper understanding of the recorded air quality metrics. The processed data is then classified using a Random Forest machine learning algorithm, which assigns each data entry to one of four predefined air quality categories. To enhance transparency and provide interpretability for health and safety operators, the SHAP method is applied, offering insights into the classification decisions and overall dataset trends. Unlike CLT-based explanations, which are omitted in this process, the system leverages well-established SHAP plots to communicate the influence of various factors on air quality predictions. The overall sequence of transformations includes retrieving numerical air quality data from Raspberry Pi air quality sensors, storing it in a comma-separated text format, transmitting it to the cloud for processing, applying a trained ML model for classification, appending it to a structured CSV file, and ultimately generating SHAP plots for explainability.

In terms of the routing application, the block diagram of the functionality in terms of data transformation is given in Figure 16.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

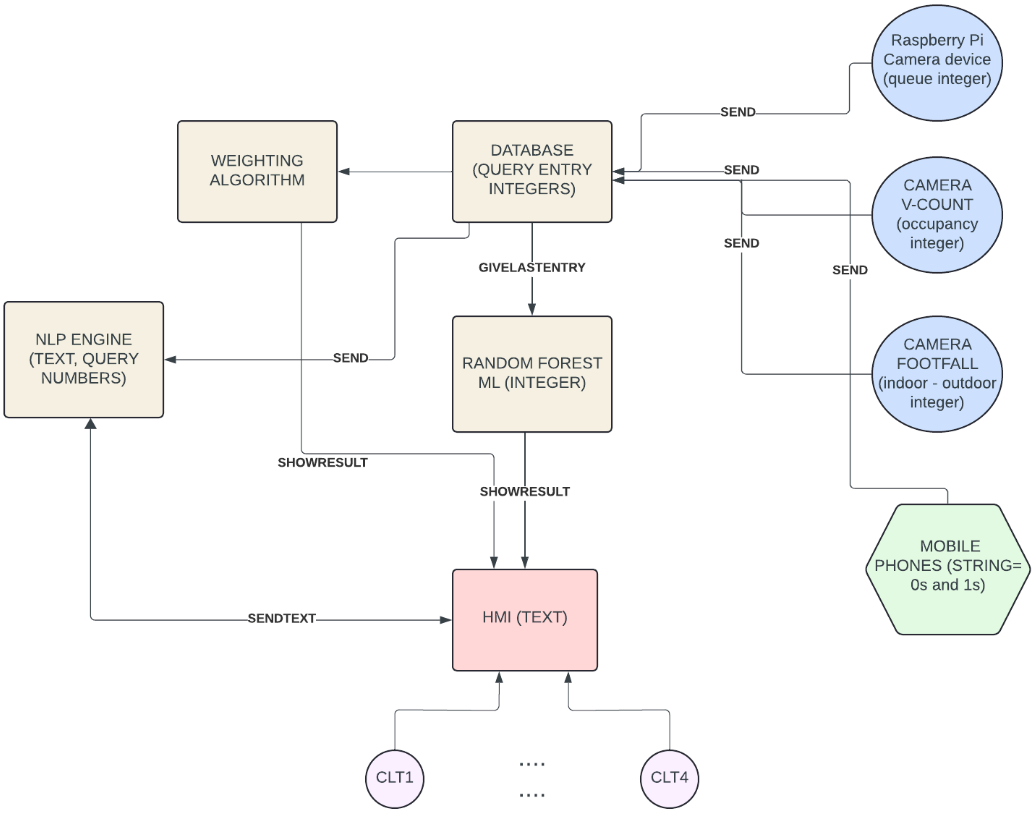


Figure 16: Routing Application block diagram

The routing application follows a structured process involving data acquisition, transformation, and analysis to optimise passenger movement within the airport. Footfall camera sensors detect the number of people entering and exiting specific areas, and by calculating the difference between these values, the system determines the occupancy levels. Moreover, the V-Count camera directly provides occupancy as a variable without requiring additional calculations. Furthermore, the Raspberry Pi prototype cameras provide a queue at each common place for queries by the passenger. Once collected, the data is transferred to the cloud database, where it is stored in predefined fields using a Python script. Note that, for synchronisation purposes, the server software resides at each prototype and the entire acquisition of the metrics occurs as a client in the cloud at a 2-minute interval. Simultaneously, passenger preferences are received via a mobile application, where selections are represented as a binary string (e.g., "1,0,0,1,0,1,1,1"), indicating the shops they wish to visit. These preferences are also stored in the database, ensuring seamless integration with occupancy data.

Once the latest data entry is available, the cloud web service triggers a Python script to execute the machine learning (ML) model, which computes the likelihood of

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

infection based on the most recent occupancy and preference data. The database then retrieves values corresponding to the selected common places (e.g., if the first position in the string is "1," it may correspond to "Shop 1"). A weighting factor is then applied to compute a risk score for each selected area. The results are displayed in text format on the HMI, forming the first level of CLT explanation. Additional CLT levels are introduced through a timer-based mechanism, which periodically updates the passenger's chatbot with explanations derived from sensor data, and weighting factor calculations. The passenger can engage with the chatbot, requesting further clarification or querying the database for more detailed insights. This dynamic interaction ensures that passengers receive real-time, data-driven recommendations, enhancing both safety and travel efficiency.

6.4. Validation 1

VAL1 was a very useful step to collect feedback and insights to refine the design of COVAID. A more specific validation of the XAI strategies and the communication models underneath will be carried out in VAL2 where feedback from actual users will be gathered to refine and improve the application iteratively.

6.5. Validation 2

COVAID's XAI was designed according to the following requirements, which were then tested during VAL2:

EASA-like EXP requirements for UC*6*
EXP-12: COVAID must be able to explain its recommendations (regarding passenger route and sequence changes) at different levels of explainability, and with progressive levels of detail
EXP-13: COVAID must be able to explain its passenger routing recommendations at different levels of abstraction, depending on both task and user properties
EXP-14: COVAID must be able to provide passenger the ability to customise levels of explainability associated with any provided recommendations
EXP-15: COVAID must be able to explain its routing recommendations (at progressive levels of detail) in a timely manner, and tailored to the user and operational properties

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

EXP-17: COVAID must provide the passengers with valid and reliable explanations, consistent with information obtained from sensors and database fields
EXP-19: COVAID must inform the passenger of any error modes, and unsafe AI based operating conditions, to make passenger aware of possibly unsafe operating conditions The system must inform the passengers of any error modes, and unsafe AI based operating conditions, to make passengers aware of possibly unsafe operating conditions. Training must cover potential unsafe operating scenarios

Table 17: EASA-like EXP requirements for UC6

The initiated VAL2 activity performed for explainability consists in

- The validation of the weighting factor values obtained by the passenger preferences and the camera sensor values. The sensor values have been double-checked for validation purposes.
- The re-routing of passengers has been tested and different values based on the predefined sensor data have been verified.
- The passenger CLT levels have been selected to include sensor data and weighting factor values to ensure trust and enhance information given to the passenger.
- The sensor failure has been mimicked to show some kind of error information to the passenger.
- The timers have been set to 15 seconds to test the CLT level timely information.
- The only customisation available to the passenger is the ability to obtain new information from the sensor data and preferences. The CLT levels have a predefined format.
- For the health and safety portal the SHAP library has been used and verified to ensure that the plots provide explainability useful to knowledgeable officers.

VAL2 allows further improvements to the UC*N* Explainability strategy and Communication model. In the following chapters 6.2 and 6.3 the final versions of the Construal levels and Communication model are presented, remarking the changes made after VAL2 (compared to the previous versions presented in D5.2 first release). The main conclusions of UC*N* on XAI are presented in chapter 6.4.

According to VAL1 and VAL2 results, the UC*6* main findings concerning XAI can be summarised as follows:

- The XAI for the air quality was provided using the standard SHAP python library plots.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

- Explanations of the plots could be beneficial for officers that cannot understand the SHAP plots.
- The CTL levels were useful for providing timely explanations to the passengers with respect to the routing application.
- CLT1 was decided that it would be the routing decision and the likelihood of infection.
- CLT2-4 were automated messages which we decided would provide information regarding the routing engine and sensor data. The primary difficulty was the implementation since it required connection to a cloud service with numerous software modules implemented to accomplish the result.
- A more personalised custom CLT process could be beneficial for the passengers. However, since this is an Android application we tried to keep things simple.
- Errors of the XAI may be provided with the faults of sensors and the output of the messages for CLT levels 3 and 4.
- Rerouting of the passenger will alter the CLT levels since the values of the sensors and passenger preferences will change giving an essence of customisation.

This project has received funding by the European Union’s Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

Conclusion

The CLT Framework emerged to be a useful tool to design XAI strategies and structure solid communication models. As the use cases develop further, the abstraction levels and communication models may change. As an example, in use case 1, where the HMI was changed and iterated during the project.

The current communication models help the use cases by addressing the information flow and detection of potential feedback loops, necessary for trust and transparency. After VAL 2, changes to CLT levels and communication have been captured (if applicable) and are reflected in each use case.

In short, the CLT framework allows information representation by structuring explanations at multiple levels of detail and allowing context-specific data queries. This approach supports decision-making in dynamic contexts by adapting information to users' needs. A few lessons learned in HAIKU to allow utilisation of the framework effectively:

- The CLT framework tends to become irrelevant in time-constrained scenarios where split-second decision making is required, such was the case in UC 1.
- The framework works well with a well-defined ConOps with clear HMI and requirements. Such was the case for UC 2 and 4.
- For cases where time is unconstrained (not infinite), such as UC 5 and 6, the framework can be adapted slightly differently. What worked well in these cases is the query and presentation of information with Chatbots or LLMs. This can further be improved with multi-modal models, which were not explored in the lifetime of the project.
- UC 3 was still too abstract for the CLT to have a meaningful contribution to developing the concept of UAM. However, the CLT structure helped shaping the ConOps with regards to the XAI strategy. The storytelling approach employed in the use case is also promising and appears to be aligned with the gradual information presentation prescribed by the CLT framework.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332

References

[1] Trope Y, Liberman N. Construal level theory. Handbook of Theories of Social Psychology 2012;1:118–34.

[2] McDermott T, Folds D. Construal level theory in the design of informational systems. Frontiers in Physics 2022;10.

[3] Nikolaidis S, Lasota P, Ramakrishnan R, Shah J. Improved human–robot team performance through cross-training, an approach inspired by human team training practices. The International Journal of Robotics Research 2015;34:1711–30. https://doi.org/10/f72r5f.

[4] Lyons JB, Sycara K, Lewis M, Capiola A. Human–Autonomy Teaming: Definitions, Debates, and Directions. Front Psychol 2021;12. https://doi.org/10.3389/fpsyg.2021.589585.

[5] Gunning D, Aha D. DARPA's Explainable Artificial Intelligence (XAI) Program. AI Magazine 2019;40:44–58. https://doi.org/10.1609/aimag.v40i2.2850.

[6] Sanneman L, Shah JA. A Situation Awareness-Based Framework for Design and Evaluation of Explainable AI. Explainable, Transparent Autonomous Agents and Multi-Agent Systems 2020;12175:94–110. https://doi.org/10.1007/978-3-030-51924-7_6.

[7] Nam CS, Lyons JB. Trust in human-robot interaction. Academic Press; 2020.

[8] Letouzé T, Blanc BL, Vennin C, Unrein H, André J-M. System maturity, distribution of tasks, and human expectations for adjustable Human Autonomy Teaming. 2024 IEEE 4th International Conference on Human-Machine Systems (ICHMS), 2024, p. 1–4. https://doi.org/10.1109/ICHMS59971.2024.10555615.

[9] Hourlier S, Diaz-Pineda J, Gatti M, Thiriet A, Hauret D. Enhanced dialog for Human-Autonomy Teaming - A breakthrough approach. 2022 IEEE/AIAA 41st Digital Avionics Systems Conference (DASC), 2022, p. 1–5. https://doi.org/10.1109/DASC55683.2022.9925736.

[10] Nonaka Ikujiro, Takeuchi H, Umemoto K. A theory of organizational knowledge creation. International Journal of Technology Management 1996;11:833–45. https://doi.org/10.1504/IJTM.1996.025472.

This project has received funding by the European Union's Horizon Europe research and innovation programme HORIZON-CL5-2021-D6-01-13 under Grant Agreement no 101075332