D2.2 - CODA - Operational services and environment description (OSED)

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Abstract

This document establishes the initial work carried out in the project, focused on:

- The definition of the State of the Art (SOA) for relevant themes touched within the project
- The presentation of use cases showing the potential application of the Controller Adaptive Digital Assistant (CODA) solution to contexts beyond the one addressed by the project (support for en-route air traffic controllers)
- The detailed description of the Operational Service and Environment Definition (OSED).

Authoring & approval

Author(s) of the document

Organisation name	Date
DBL	01/10/2023
ENAC	08/12/2023
CRIDA	08/12/2023
UPM	08/12/2023
NLR	13/11/2023
ECTL	08/12/2023
UGR	08/12/2023

Reviewed by

Organisation name	Date
ENAC	18/12/2023
BS	18/12/2023
CRIDA	18/12/2023
UPM	18/12/2023
NLR	18/12/2023
ECTL	18/12/2023
IFATCA	18/12/2023
UGR	18/12/2023

Approved for submission to the SESAR 3 JU by[1]

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DBL	21/12/2023
ENAC	21/12/2023
BS	21/12/2023
CRIDA	21/12/2023
UPM	21/12/2023
NLR	21/12/2023
ECTL	21/12/2023

[1] Representatives of all the beneficiaries involved in the project

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[2] Representatives of the beneficiaries involved in the project

CODA

Controller Adaptive Digital Assistant

CODA

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Table of contents

List of tables

List of figures

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1 Executive summary

STATE OF ART. The project is built upon **the most recent achievements from research and literature** on Human AI teaming, real time objective assessment of ATCOs mental states, prediction of incoming tasks and their impact on mental states, adaptation strategies for human AI systems, the state of the art for explainable systems and on the outcomes of previous SESAR projects (such as the STRESS project, the MINIMA project, the eCOMMET project, the COTTON project, and other project focused on AI based adaptable and explainable systems such as ARTIMATION, MAHALO, AISA and the HAIKU project).

GENERIC USE CASES. Although the project will focus on the en-route controller use case, the proposed solution is expected to be applicable in the future also to **other relevant contexts** which have been identified thanks to the support of external experts (e.g. tower ATCOs, Approach ATCOs). At the same time, although the solution as prototyped in the project will make use of a limited set of AI digital assistants interventions and will focus on specific scenarios, several future use cases enabled by the CODA solutions has been identified with the help of end users, such as: Storm Deflection Symphony (Advancing Human-AI Collaboration for Dynamic Air Traffic Management), Navigating Turbulence (Enhancing Adaptive Automation for Seamless Human-AI Collaboration in Adverse Weather Conditions), Harmony in Complexity (Advanced Human-AI Collaboration in Dynamic Air Traffic Management with Enhanced Weather Integration), Dynamic Conflict Resolution and AI Delegation in Air Traffic Management and AI Enhanced Air Traffic Control (Dynamic Adaptation in High-Stress Situations).

CODA OSED. The overall objective of the CODA project is **to increase ATM's efficiency, capacity, and safety**, maximising human-AI teaming by developing a system in which tasks are performed collaboratively by hybrid human-machine teams and dynamically allocated through adaptive automation principles. To do so CODA focus on developing a solution that predict relevant mental states of en-route air traffic controllers so to anticipate possible problems and trigger specific actions (such as the activation of Digital Assistants).

The improvements proposed by the CODA project will impact the Air Traffic Controllers (ATCOs) work in an **en-route sector with a congested traffic situation environment.** The solution could enable some changes in tasks and roles of ATCOs, which are investigated by the project but not strictly defined, as this will be highly impacted by the technical environment that will be available in the future (e.g. highly automated tools, AI digital assistants).

CODA starts from some high-level **assumptions**: i) real time assessment of ATCOs mental states is allowed; ii) reliable AI based Digital Assistants will be available to carry out both routine tasks and more complex ones (including decision making and actions execution)

It is expected that the project will have an impact on different **stakeholders** within the ATM domain (ANSPs, Airspace Users) in terms of:

- Human performance: Exploiting automation up to its higher levels to perform non-critical tasks, adapting the human-machine interface with different explainability levels, and foreseeing and preventing possible problems are expected to **reduce ATCOs' workload and enhance their performances**.

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- Efficiency, capacity and safety: the developed AI system will then provide the additional capacity to meet the challenges of increasing air traffic complexity due to sustained growth and new airspace users and support **more efficient and environmentally friendly operations while maintaining and improving current safety levels.**

The CODA project will start with a TRL (Technology Readiness Level) 1 , and it sets the goal of achieving a **TRL 2** by the end of the work.

The CODA solution is **an enabler for adapting systems** based on AI tools and other types of automation. Once the feasibility of the concept is confirmed within the current project, further steps would be: i) to Investigate the use of the system also in other relevant use cases (such as Tower controllers, TMA controllers) ii) to assess the precise impact on KPIs once the system is actually connected to Digital Assistants (out of scope for this project).

2 Introduction

2.1 Purpose of the document

This document provides the specifications covering the State of the Art (SOA) related to the main topics addressed in the CODA project and defines the Operational Service and Environment Description (OSED) of the project. The document describes in detail:

- The State of the Art which covers:
  - State of the art for Human-AI interaction
  - State of the art for operators' state assessment
  - State of the art for task prediction models
  - State of the art for mental states prediction
  - State of the art for adaptive systems
  - State of the art for explainable systems
- The definition of generic use cases
- The Operational Service and Environment Definition (OSED) which describes:
  - Operational characteristics
  - Roles and responsibilities
  - CNS/ATS description
  - Applicable standards and regulations
  - Previous and new SESAR operating method
  - CODA use cases

The document is completed by the Appendix, which includes the Cost and Benefit Impact Mechanisms. The implementation of its content shall present how the SESAR Solution elements contribute (positively or negatively) to the delivery of performance benefits and costs.

This document defines the operational service and environment (OSED) for CODA at TRL2.

2.2 Scope

As stated above, the purpose of this document is to present the CODA Operational Service and Environment Description (OSED) and to provide the result related to the first two tasks of the **WP2 - Adaptive automation state of the art and use cases definition**, namely T2.1 State of the Art and T2.2 Operational concept and use cases definition.

The work contained in this deliverable is closely linked to the deliverable D2.2 FRD – Functional Requirements Document which will detail the CODA system functional description and the necessary logical interfaces with other systems, covering functional and interface requirements.

2.3 Intended readership

The intended audience for this document primarily consists of all the partners involved in the CODA project.

External to the SESAR project, other stakeholders are to be found among:

- ATM Stakeholders:
- ANSPs (Air Navigation Service Providers)
- ATM infrastructure and equipment suppliers
- Airspace users
- Airport owners/providers
- Affected National Supervisory Authorities (NSA)
- Affected staff organisations
- Regulatory and standard organisations:
    - EASA
    - ICAO
    - European ATM Standards Coordination Group (EASCG)
    - EUROCAE
- Other Single European Sky ATM Research (SESAR) solutions partners.

2.4 Background

The CODA project aims to demonstrate the feasibility of developing a system in which tasks are collaboratively performed by hybrid human-machine teams and dynamically allocated through adaptive automation principles.

To achieve this goal, the project **consolidates the work previously undertaken in the SESAR Exploratory Research projects.** The findings from ARTIMATION and MAHALO will be utilized to develop an AI-based adaptable and explainable system, allowing the system to proactively prevent future performance or safety issues. The outcomes of MINIMA and STRESS will be employed for a neurophysiological assessment of mental states. This will enable the system to discern operators' real-time levels of workload, attention, stress, fatigue, and situation awareness. The results from COTTON and eCOMMET will contribute to the development of prediction models, anticipating future situations. This enables the system to understand which activities will be undertaken by operators in the future and their potential impact on human factors.

2.5 Structure of the document

This document has the following structure:

Chapter 1 (Executive summary): contains a brief description of the document.

Chapter 2 (Introduction): contains the purpose, the scope, the intended readership, the background, and the structure of this document. Further significant information such as glossary of terms and list of abbreviations have been included at the end of the chapter.

Chapter 3 (State of the art): given the overall objective of enhancing efficiency, capacity, and safety in Air Traffic Management (ATM) through optimizing Human-AI collaboration, in this chapter the primary goal is to assess the latest advancements at the forefront of research and development across various domains. These include reviewing the current state of the art of Human-AI teaming, operators' state assessment, tasks prediction models, mental states prediction models, adaptive systems, and explainable systems.

Chapter 4 (Generic use cases): This section provides a list of possible use cases of application of the proposed CODA project in the aviation domain.

Chapter 5 (Operational service and environment definition): This chapter describes the SESAR solution under the scope of the document, detailing the operational environment and operational concept aspects.

Chapter 6 (Key assumptions): here are provided the key assumptions related to relevant topics addressed by the project CODA, such as key assumptions for models' development and key assumptions related to future AI systems.

Chapter 7 (References): the references, and applicable documents.

Appendix A: describes the Cost and Benefit mechanisms applied to the CODA project.

2.6 Glossary of terms

Term	Definition	Source of the definition
Air Traffic	All aircraft in flight or operating on the maneuvering area of an aerodrome.	ICAO Annex 11 - ATS
Air Traffic Controller	• Qualified in accordance with ICAO Annex 1 – Personnel Licensing and holding a rating appropriate to the assigned functions, • A person authorized to provide air traffic control services.	EUROCONTROL ATM Lexicon
Air Traffic Management	The dynamic, integrated management of air traffic and airspace including air traffic services, airspace management and air traffic flow management – safely, economically and sufficiently – through the provision of facilities and seamless services in collaboration with all parties and involving airborne and ground-based functions.	ICAO 4444 - ATM
Air Traffic Services	A generic term meaning variously, Flight Information Service (FIS), Alerting Service (ALRS) and Air Traffic Control Service (ATC) (area control service, approach control service or aerodrome control service). In this document, when the term ATS is used, it is usually referring to TWR or AFIS.	ICAO, Annex 11
Sector	A part of a control area and/or part of a flight information region or upper region.	EU 2015/340

Table 1: glossary of terms

2.7 List of acronyms

Term	Definition
AI	Artificial Intelligence
AISA	AI Situational Awareness Foundation for Advancing Automation
ANSPs	Air Navigation Service Providers

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ARTIMATION	Transparent Artificial Intelligence and Automation to ATM Systems
ATCo	Air Traffic Controller
ATCS	Air Traffic Control System
ATM	Air traffic management
ATS	Air traffic services
BDI	Beliefs Desires Intention
BIM	Benefit Impact Mechanism
CNS	Communication Navigation Surveillance
CNS	Central Nervous System
COCOM	Cognitive Control Model
CODA	Controller Adaptive Digital Assistant
ConOps	Concept of Operations
COTTON	Capacity Optimisation for Trajectory Based Operations
CPDLC	Controller and Pilot Data Link Communication
CSE	Cognitive Systems Engineering
DES	Digital European Sky
EASA	European Union Aviation Safety Agency
EBA	Eyeblink Amplitude
EBD	Eyeblink Duration
EBR	Eyeblink Rate
ECG	Electrocardiography
ECOM	Extended Control Model
eCOMMET	enhanced COMplexity ManagEment Tool
EDA	Electrodermal Activity
EEG	Electroencephalography
EOG	Electrooculography
ERP	Exploratory research plan
eTLM	Enhanced Traffic Load Monitoring
GA	Grant agreement
GDPR	General data protection regulation
HAIKU	Human AI teaming Knowledge and Understanding for aviation safety
HAIT	Human-AI Teaming
HE	Horizon Europe
HMPE	Human Machine Performance Envelope
HR	Heart Rate
HRV	Heart Rate Variablity
ID	Identifier
JCF	The Joint Control Framework
LACC	Levels of Autonomy in Cognitive Control
LOAs	Levels of autonomy
MAHALO	Modern ATM via Human/Automation Learning Optimisation
MINIMA	MItigating. Negative Impacts of Monitoring high levels of. Automation
MSAW	Minimum Safe Altitude Warning

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MTCD	Medium Term Conflict Detection
MUFASA	Multidimensional Framework of Advanced SESAR Automation
OBJ	Objective
OOTL	Out-of-the-loop
OSED	Operational service and environment description
PFC	Pre-Frontal Cortex
PM	Process Mapping
PPC	Posterior Parietal Cortex
PPG	Photoplethysmography
PPP	Perceived Privacy Protection
SA	Situation Awareness
SAT	Situation Awareness-based Agent Transparency
SCL	Skin Conductance Level
SCR	Skin Conductance Response
SESAR	Single European sky ATM research
SESAR 3 JU	SESAR 3 Joint Undertaking
SNS	Sympathetic Nervous System
SOA	State of the Art
SRIA	Strategic research and innovation agenda
STCA	Short Term Conflict Alert
STRESS	Human Performance neurometricS Toolbox foR highly automatEd Systems deSign
TBO	Trajectory-Based Operations
TID	Touch Input Device
TRL	Technology Readiness Level
UAM	Urban Air Mobility
XAI	Explainable AI

Table 2: list of acronyms

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3 State of the art

This chapter presents the results of a preliminary study to set the basis for the work in the CODA project. A list of relevant topics has been generated, and a look at the state of the art in terms of literature, research projects and related solutions in the aviation domain has been carried out. The objective is:

- To define the concepts that will be addressed in the project (see the green circles in the following image)
- To highlight the most advanced results in terms of technology, knowledge, and methods in the different fields from which the project will start to perform the foreseen work
- To show where the project will improve concerning the SOA

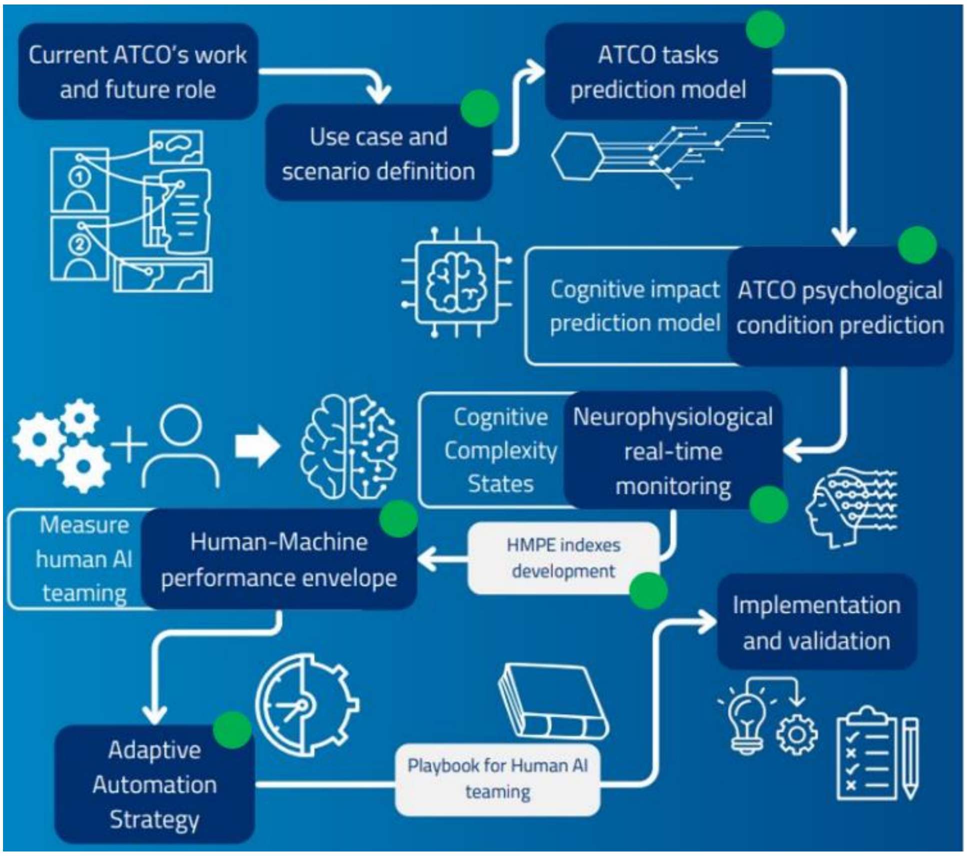


Figure 1: Overview of project structure. The contents highlighted by the green circles are the ones introduced and defined in this deliverable

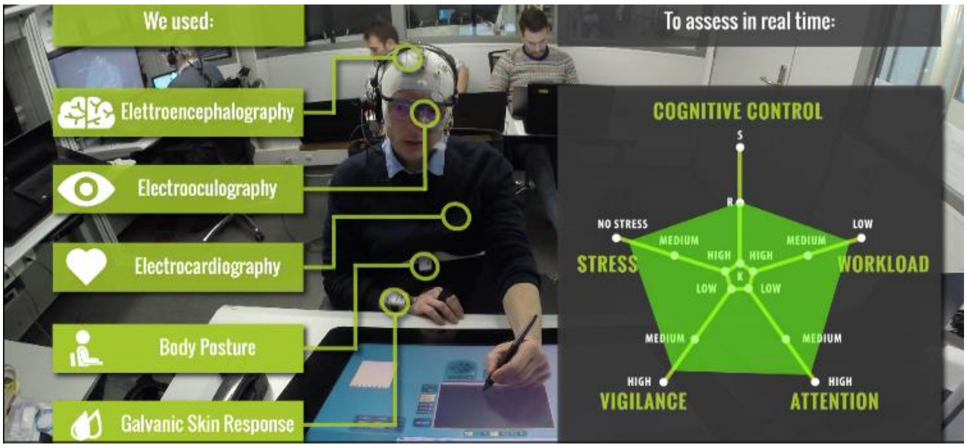
3.1 Relevant research projects

The following projects cover different technologies, techniques and systems that are relevant for the CODA project. All the projects cover one or more of the following topics:

1) **assessing operator status** to provide valuable insights for adapting automation levels to the current mental state of operators. These projects highlight the importance of understanding and adapting to the mental states of operators in high-stress, high-automation environments, offering valuable insights for the development of adaptive automation systems in the field of Air Traffic Management.
2) **identifying forthcoming controller tasks and mental workload**, ultimately contributing to the optimization of human-AI interactions within the realm of air traffic management (in particular eCOMMET and COTTON projects).
3) **assessing operator status and AI transparency**, aiming to strike a balance between optimized AI solutions and the need for explainability and user understanding. The insights gained from these projects provide valuable design guidelines for enhancing transparency and customization in AI systems, ultimately influencing their acceptance and usability by Air Traffic Controller (ATCos). These findings will greatly assist CODA in defining how to deliver predictions to users, determine the appropriate level of detail, and suggest effective interactions with AI tools to ensure a seamless and productive human-AI teaming experience.

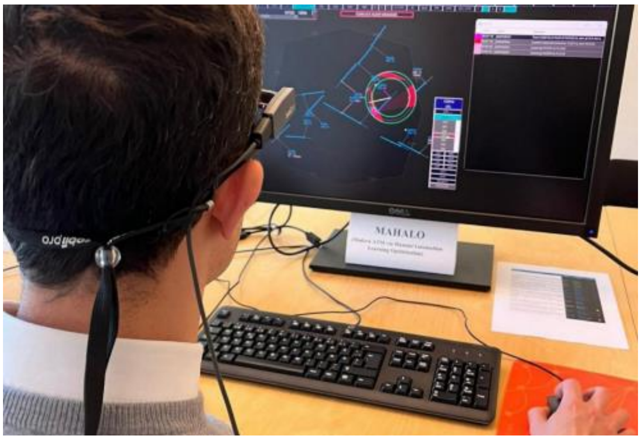
A brief description of the relevant projects is provided below.

- The STRESS (2018) project explored the impact of advanced highly automated systems on en-route ATCos performance to support the ATCos in future ATM operational scenarios. By using real time assessment of stress, workload and vigilance data coming from ATCos interacting with highly automated systems, the STRESS project developed a set of guidelines to be applied in designing a personalized neurophysiological measurement toolbox to optimize performance and safety for Air Traffic Controllers (ATCos). The outcomes derived from this project will be used during the CODA project to derive a new HMPE index, based on both the neurophysiological and predicted internal states of the operator.



- The MINIMA (2018) project investigated the possible negative effect of too much automatism on vigilance and Situation Awareness (SA) due to high levels of automation in future ATM scenarios. This phenomenon is called “Out of the loop (OOTL)”. During the project, it has been developed and validated a neurophysiological index based on EEG activity of the controller. By monitoring the controller's vigilance variation, this index can identify in real time loss of attention of the controller, triggering online an adaptive automation system, capable to intervene and so mitigate the OOTL phenomenon and possible mind wandering effect. In CODA this index will be used to calibrate from one side and to feed from the other side the predicted model regarding the future state of the operator.

- eCOMMET (2019) - Cognitive Complexity Tool to refine demand and capacity measures. The results will help CODA by providing a first model that can be expanded to identify the future mental state of the controller. (Final Report https://cordis.europa.eu/project/id/731730)
- The COTTON (2018) - Capacity Optimisation for Trajectory Based Operations - project addressed the analysis and quantification of complexity in a Trajectory-Based Operations (TBO) environment considering the future SEAR solutions. It proposed innovative solutions for integrating predicted trajectories' uncertainty within the complexity and workload assessment methods and the Capacity Management processes. The results of this project will help CODA identify the future controller tasks and the associated mental workload. (Final Report https://cordis.europa.eu/project/id/783222)
- The MAHALO (2022) - Modern ATM via Human/Automation Learning Optimisation 2022- project examined strategic conformance and transparency in human-AI interaction, aiming to balance optimized AI solutions that require explainability with conformal AI solutions easily understood by Air Traffic Controllers (ATCos). Results provided design guidelines, highlighting that greater transparency can enhance understanding but may not guarantee system acceptance. Customized transparency, with AI adapting to user needs, can lead to deeper understanding and acceptance. The project emphasized hybridizing ML and adaptive systems to enhance automation, affecting task performance and responsibility distribution between humans and AI. The level of automation significantly impacts human-AI team performance in various situations. The project results will help CODA in defining how to deliver the predictions to users, the level of detail and the suggested actions.



- The ARTIMATION (2022) - Transparent Artificial Intelligence and Automation to ATM Systems - project evaluated the influence of various visualization techniques for ATM CD&R and delay prediction algorithms and investigated and explored the differential human performance impacts on expert and student controllers. Results showed that explanations should be delivered on demand and should be integrated into the system and not available on external systems. Air Traffic Controllers (ATCos), when facing pressure, don't always have time to thoroughly examine explanations from the AI. These results will help CODA when defining how the proposed AI tools will interact with the users, to guarantee a good human-AI teaming.

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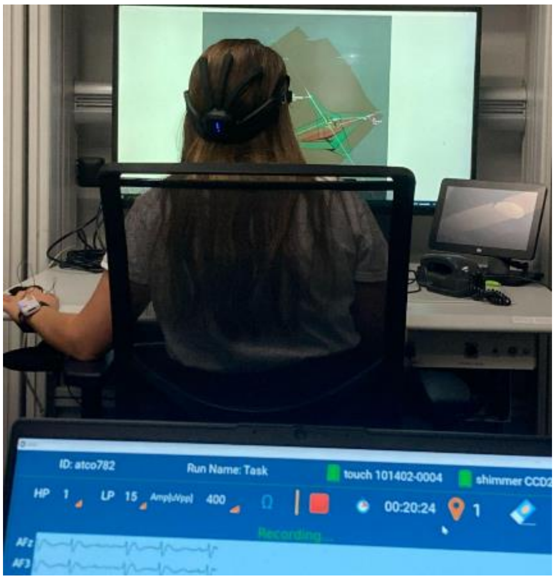
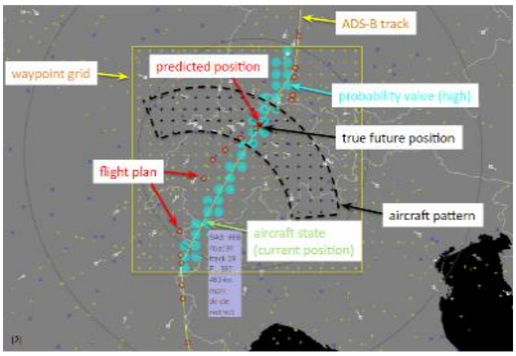


- The AISA (2022) project: By developing an intelligent situationally aware system AISA proposed a solution geared towards improving collaboration between humans and machines within the air traffic control environment. The project also addressed the issues of transparency and generalization, presenting a vision for automation within the en-route Air Traffic Control (ATC) operational environment. Although the project contributed to develop an intelligent situation-aware system that enables the same team SA to be shared between controllers and AI, the system still faces an issue which is the ability to analyse the controller's intent to provide adaptable assistance to the controller. Thus, the AISA project lays the fundamental groundwork for the CODA project in creating a mindful digital assistant. However, the CODA project will need to consider these limitations, considering the air traffic controller's intent.



- The HAIKU (2025) project: an ongoing project that focuses on Human-AI teaming is HAIKU. Its main objective is to deliver prototypes of AI Digital Assistants for different aviation segments and users, by developing guidance and assurance procedures, and by exploring Human-AI Teaming via several interactive prototypes. Within the context of human-AI teaming, it aims to design human-machine teaming for the different aviation applications (cockpit, ATM, UAM, airport) to extend the system performance envelope, considering timeframe of operations, complexity, type of involved human tasks, criticality.

The framework for Human-AI teaming that will be proposed in HAIKU will help CODA in designing the automated digital assistant.

3.2 State of the art for Human-AI interaction

3.2.1 Human-Machine interaction and Human-AI teaming: a first definition

As stated in the Description of the Action (see 101114765 CODA Grant Agreement Annex 1 (Part B), "The strategic objective of the CODA project is to increase the efficiency, capacity, and safety of ATM maximising Human-AI teaming by developing a system in which tasks are performed collaboratively by hybrid human-machine teams and dynamically allocated through adaptive automation principles.".

Therefore, the first step is **to define what Human-AI teaming is, what are the current available methods to describe and achieve it, and what has been done so far in terms of research,** especially in the aviation domain.

The first thing to be highlighted is that, when dealing with AI, the research community moved from "Human-Machine" to "Human-AI", and from "interaction" to "teaming", somehow stressing the fact that, when dealing with AI-powered solutions, **a different approach should be considered to design how humans should use those systems**. The term "human-AI teaming" describes the collaboration between humans and artificial intelligence (AI) systems. It's unclear who specifically coined the term, but it's now widely used in AI research and development field.

Human-AI interaction refers to **the dynamic interplay between individuals and AI-powered machines or algorithms**, encompassing a wide range of activities from using voice-activated virtual assistants to receiving personalized recommendations on digital platforms (Berretta et al., 2023). This interaction has significantly reshaped how we access information, make decisions, and perform tasks, ultimately augmenting our capabilities.

While human-AI interaction represents the interface through which we engage with AI, the concept of human-AI teaming takes this interaction to a higher level of collaboration and synergy. The concept involves AI systems taking on roles and responsibilities within a team, functioning interdependently with human team members. This term expresses a system that expands from one-human-one-machine (e.g., a human-AI interaction or a human-robot interaction) to a team of more than two heterogeneous entities, each with their roles and responsibilities. Human-AI teaming involves humans and AI systems working together as cohesive units, combining their strengths to achieve common goals. This collaborative approach acknowledges the unique abilities of each entity, where humans contribute contextual understanding, creativity, and ethical judgment, while AI brings computational power, data analysis, and automation (National Academies of Sciences, Engineering, and Medicine, 2022). Human-AI teaming is not merely about humans using AI as tools but rather **a collaborative partnership that leverages the strengths of both parties to enhance decision-making, problem-solving, and overall performance**. Human-AI teaming holds immense significance in various fields, including aviation, healthcare, and manufacturing, as it offers the potential for increased efficiency, accuracy, and innovation. What sets human-AI teaming apart from traditional human-AI interaction are factors such as shared mental model and adaptive learning. In teaming, AI systems can adapt to human preferences and vice versa, leading to more fluid and effective cooperation. Furthermore, the synergy between humans and AI in teams allows for more complex problem-solving and the tackling of challenges that neither could handle alone (Flathmann et al., 2023).

Since there is no single, conclusive definition of Human-AI teaming that can provide a reference framework for the CODA project, Human-AI Teaming will be considered as: **"The collaborative partnership between human operators and AI applications, wherein AI applications provide support to human operators while maintaining transparency by involving them in the decision-making and reasoning processes".**

This includes the AI system predicting the future mental state of the operator and adapting its automation strategy accordingly.

3.2.2 Factors contributing to good Human-AI teaming

Having provided the definition of Human-AI teaming, the next question is which factors influence the teaming with AI solutions. For an effective interaction and a successful teaming of humans and AI agents, multiple factors must be considered.

Trust is one of the crucial factors that are essential for the acceptance and utilization of AI as a team member (Hagos and Rawat, 2022; National Academies of Sciences, Engineering, and Medicine, 2022; Pinto et al., 2022). To build trust, human operators need to have enough information about the system to understand when they can rely on AI and when they cannot (McDermott et al., 2018). Failing to adjust the right level of trust can result in either avoidance or over-reliance on the intelligent agent (Parasuraman & Riley, 1997; Robinette et al., 2016).

Another significant factor for proper operation of Human-AI teams is **agency**, which is defined as the authority and capability of an agent to act based on their own discretion and timing (Lyons & Wynne, 2021; Schlosser, 2019). Agency is considered the crucial distinctive characteristic that separates autonomy from automation. It transforms the role of intelligent systems from an assistant who follows instructions to a teammate who can take the initiative and make decisions independently (Lyons et al., 2021).

Task allocation and **interdependency** is the next significant concern that must be properly addressed (Ali et al., 2022). What must be carefully considered is the type and extent of interdependence in a team of humans and machines. The interaction between humans and AI agents can happen at different levels, from no coexistence to close collaboration (Aaltonen et al., 2018). Task allocation endeavours must consider not only the level of collaboration, but also the interdependence of tasks in order to make sure both parties have a collective commitment to achieve the objectives and share the teamwork across the tasks (Lyons et al., 2021).

Another important attribute of successful human-AI teams is their **adaptability**, which implies the capability to respond adaptively to changing environmental factors and task requirements (Mosier et al., 2017). Operators should be able to modify the extent of support offered by AI (i.e., adaptable automation) and, also, the intelligent agent should have the capability to predict the change in knowledge and behaviour of operators and adjust their workload and the extent of their assistance

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accordingly (i.e. adaptive automation) (Hagos & Rawat, 2022; Miller et al., 2005; Mosier et al., 2017; Oppermann, 1994).

Communication and **coordination** are two interconnected factors essential for the proper performance of any human-AI team (National Academies of Sciences, Engineering, and Medicine, 2022; Panagou et al., 2023). Communication has a vital role to play in supporting work procedures, fostering interdependencies among team members, and facilitating the cultivation of shared situation awareness, shared mental models, and goal alignment (Lyons et al., 2021). Communication in Human-AI teams must be coordinated, which means it should be precise and appropriately targeted to the correct team member at the correct time. Successful teamwork requires adeptly orchestrating the sequencing and timing of interdependent actions (National Academies of Sciences, Engineering, and Medicine, 2022).

A crucial prerequisite for optimal team performance involves team members' congruent understanding of their tasks, teamwork procedures, and the operational context. This concept is commonly referred to as a "**shared mental model**" (Mosier et al., 2017). Sharing mental models empowers human-AI teams to proactively predict team needs, actions, and upcoming challenges (Lyons et al., 2021). Shared mental models within teams contribute to the development of **shared situation awareness**. It is commonly recognized that effective interaction between humans and AI systems requires robust situation awareness (SA). This encompasses the understanding of both present and predicted performance, status, and information possessed by each entity (National Academies of Sciences, Engineering, and Medicine, 2022).

Effective human-AI teaming necessitates a high level of **transparency** in intelligent systems. The concept of transparency comprises several facets, such as organizational transparency, process transparency, data transparency, algorithmic (logic) transparency, and decision transparency (National Academies of Sciences, Engineering, and Medicine, 2022). The facet of transparency that facilitates human oversight and cooperation with AI systems is referred to as system transparency, defined as "the understandability and predictability of the system" (Endsley et al., 2003, p. 146). System transparency comprises two interrelated components: **Display transparency**, which provides real-time visibility into the ongoing operations of the AI system, enhancing situation awareness (SA); **Explainability**, which offers retrospective insights into the system's actions or recommendations, elucidating the underlying logic, processes, factors, or reasoning (National Academies of Sciences, Engineering, and Medicine, 2022).

The solution proposed by CODA will impact mainly on task allocation, interdependency, adaptability, situation awareness, and transparency.

3.2.3 Consequences of bad Human-AI teaming

In a safety-driven domain such as aviation, a better understanding of how Humans and AI should collaborate is crucial so to avoid the consequences of a bad design of Human AI teaming, especially in terms of performance, safety and operators' wellbeing. Bad Human-AI Teaming can have significant consequences that extend beyond the immediate collaboration between humans and artificial intelligence (AI) systems.

One prominent consequence is the potential for detrimental effects on team performance (Bienefeld et al., 2023). When human-AI teams fail to function cohesively and synergistically, it can result in inefficiencies, errors, and decreased productivity (Nols et al., 2023). Poor collaboration may lead to misunderstandings, conflicts, and suboptimal decision-making, which, in turn, can negatively impact overall team outcomes (Bezrukova et al., 2023).

Automation complexity can lead to operator confusion and unrealistic expectations (Endsley, 2019). Further, when automation functions correctly, people may become complacent, but high workload situations can overwhelm them (Bainbridge, 1983). Overseeing automated systems can result in slower problem identification and understanding, primarily due to reduced situational awareness, and this can result in catastrophic consequences in novel or unexpected situations (Sebok & Wickens, 2017). Research has shown that human decision-making can be influenced by automated errors (Endsley and Jones, 2012). As an illustration, the 2009 Air France Flight 447 accident highlights the critical nature of human-AI collaboration while also serving as a reminder of the potential consequences that can arise when such teaming is not properly addressed. The Air France Flight 447 accident in 2009 revealed the difficulties posed by the complexity of the situation, including severe weather conditions and airspeed sensor malfunctions. Unrealistic expectations about the Airbus A330's automated systems led to complacency and a decline in manual flying skills. The crew's reduced situational awareness and failure to identify the stall condition, coupled with inadequate guidance by the automated system, resulted in slower problem recognition. Additionally, the influence of autopilot's recommendations on decision-making, even when those recommendations were inappropriate, demonstrated the complex dynamics of human-AI teaming. These factors contributed to the tragic consequences of the accident.

Additionally, safety concerns arise when human-AI teaming is subpar. A lack of effective collaboration can result in safety hazards, especially in critical domains such as healthcare or aviation (Zhang et al., 2023). Miscommunications, misinterpretations, or AI system errors can lead to unsafe practices or decisions that jeopardize the well-being of individuals or the integrity of systems. Thus, bad human-AI teaming not only hampers performance but also poses risks to safety, underscoring the importance of fostering effective collaboration in these partnerships.

To harness the full potential of human-AI collaboration while ensuring safety, it is essential to address and mitigate the challenges associated with suboptimal teaming dynamics (Pflanzer et al., 2023).

3.2.4 General methods and models

In recent years, extensive research has explored the complex dynamics of human-AI teaming across different domains, resulting in the development of descriptive models, theoretical frameworks, and best practices derived from real-world experiences in human-automation teaming. These findings offer a comprehensive insight into the evolving landscape of human-AI collaboration. The descriptive models provided in this research context include various aspects, such as the integration of AI systems into team structures, the allocation of tasks and responsibilities between humans and AI agents, and the influence of AI on team communication and decision-making processes.

3.2.5 A definition for teaming

In the broader context of team studies Salas et al. (1995) define teams as groups united by common goals, roles, and interdependence. Additional team characteristics that have been identified in this body of research include decision making within a task context, specialized task-related knowledge and skills, and performance within the task-context constraints of time pressure, workload, and other conditions, with **mental models** playing a crucial role in task-related knowledge representing how team members organize and interpret information.

Cooke et al. (2007) emphasize further the interdependent nature of team dynamics, highlighting the need for **coordination** among members.

3.2.6 Principles for Human-AI teaming

As anticipated in the beginning of this chapters, many authors have specifically focused on the study of teams involving humans and automated systems, and they have provided definitions for this type of team. For example, Cuevas et al. (2007) define human-AI teams as "one or more people and one or more AI systems requiring collaboration and coordination to achieve successful task completion." An easily applicable definition in the context of Human-AI teaming is provided by McNeese et al. who characterize a human-autonomy team as **a team where humans and autonomous agents operate as coordinated units.**

Recently, the National Aeronautics and Space Administration has outlined three fundamental principles for human-autonomy teams: (1) bi-directional communication about mission goals and rationale; (2) transparency regarding what the automation is doing and why; and (3) operator-directed interfaces for dynamic function allocation (Brandt et al., 2018).

Forbus (2016) emphasizes the importance of AI possessing autonomy, a shared focus with humans, natural language understanding, and effective interaction skills, while Boardman & Butcher (2019) strongly highlight that in order to have meaningful control, the human must have (1) freedom of choice; (2) the ability to impact the behaviour of the system; (3) time to engage with the system and alter its behaviour; (4) sufficient situation understanding; and (5) the ability to predict the behaviour of the system and the effects of the environment.

Since it is crucial for human operators to accept artificial intelligence systems as true teammates, authors such as Wynne and Lyons (2018) focused on understanding how humans perceive autonomous partners, emphasizing the concept of "autonomous agent teammate-likeness" and exploring how humans view AI as more than just tools, perceiving them as altruistic, benevolent, interdependent teammates.

However, according to the National Academies of Sciences, Engineering, and Medicine, 2022 although there has been some work, particularly using descriptive models, to describe the elements and factors relevant to human-AI teaming, to date **none of these efforts has progressed toward computational models or quantifications of the relative importance of team characteristics, processes, or other factors.**

3.2.7 Potential high-level integrated frameworks for HAIT

Nevertheless, at present high-level approaches that are suitable candidates to use in the analysis and design of Human AI teaming systems do exist.

Cognitive Systems Engineering (CSE) is an approach aimed at modelling and comprehending complex human-machine systems at a cognitive level, specifically focusing on cognitive functions. It involves modelling these systems as adaptive entities that respond to feedback inputs to adapt and ensure control over processes. Recently, this method has been used by Malakis et al., (2023) to develop a framework of six cognitive functions for supporting adaptive human-AI teaming in Air Traffic Control, including: steering or goal setting, sensemaking and mental models, common operating picture or shared mental models, coordination and transfer of control, managing changes, and operating or planning-doing-checking cycle.

In the Cognitive Control Model (COCOM) three basic concepts are central: competence, control, and constructs. **Competence** represents the set of possible actions or responses that the joint system can take to a situation according to the recognised needs and demands. **Control** characterises the orderliness of performance and the way in which competence is applied in relation to the immediate and long-term goals, and this is time dependent. **Constructs** refer to what the system knows or assumes about the situation in which the action takes place (Hollnagel, 2000).

In an extended version of COCOM, ECOM (Extended Control Model), Hollnagel introduces several control loops and modifies the model to include different levels of control that, basically, represent a scale from low level regulation to planning control (skill-based, rule-based and knowledge-based control actions). In characterising ECOM, Hollnagel pictures four stacked control loops. There can be interaction between control loops and each control loop can be suspended. Automation can assume control over one or more of these loops, and performance can be either open- or closed-loop. The two models are depicted in the figure below.

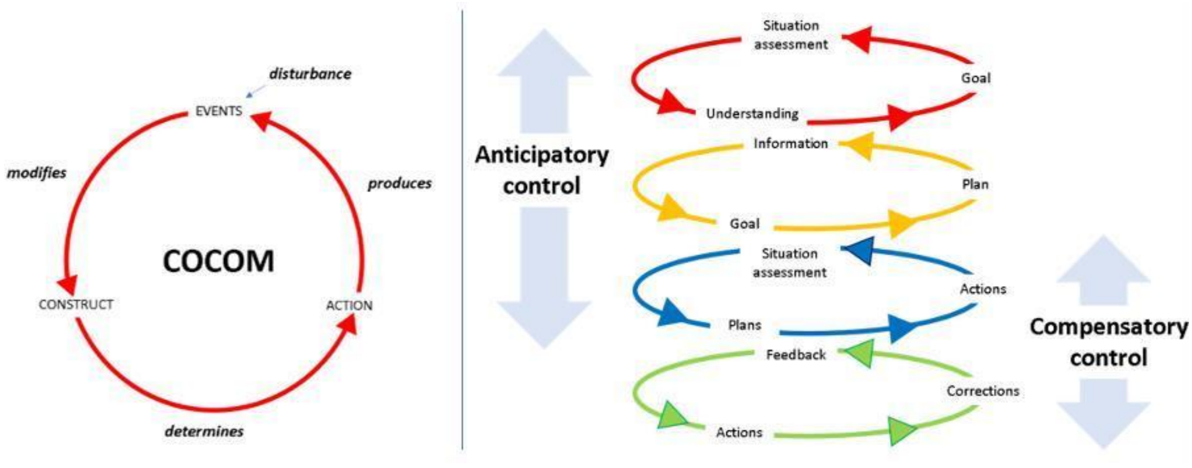

Figure 2: The Cognitive Control Model (COCOM) and Extended Control Model (ECOM) (after Hollnagel, 2000)

PRODEC (Boy & Morel, 2022) is a recent framework and method for designing human-machine teaming, aiming to integrate procedural and declarative methods and focusing on procedural as well as problem-solving skills for both humans and machines. PRODEC has been used and validated in the MOHICAN project, which focused on the integration of pilots and virtual assistants onboard advanced fighter aircraft. This application enabled the development of relevant metrics and criteria related to performance, trust, collaboration, and tangibility, addressing aspects such as complexity, maturity, flexibility, stability, and sustainability.

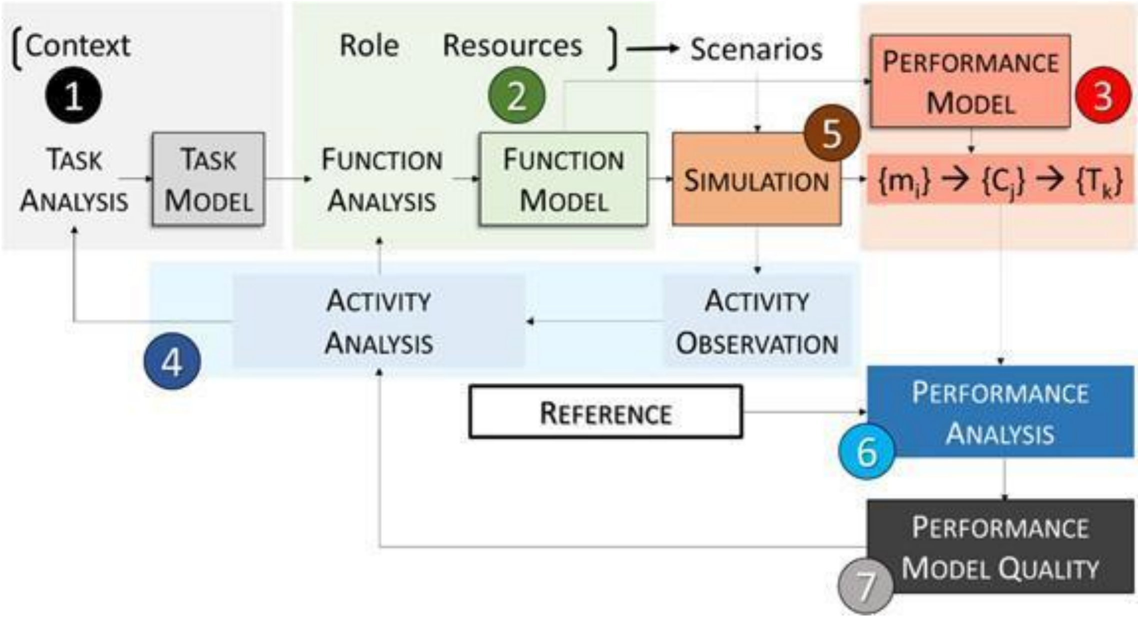

Figure 3: Methodology for performance assessment of a multi-agent system (Boy & Morel, 2022)

Importantly, it is one of the few frameworks that explicitly address Human-AI teaming and it is useful for the analysis, design, and evaluation of a complex sociotechnical system.

The Joint Control Framework (JCF) can be seen as an extension of the theories based on abstraction layers and cognitive functions as the unit of analysis (Lundberg & Johansson, 2021). The framework can be used to describe critical episodes of interaction between human operators and autonomous, automated, and manual control systems. A JCF analysis considers cognitive control levels (functions), temporal aspects of control, and communication and control at the system joints. A JCF analysis typically includes process mapping (PM), analysis of Levels of Autonomy in Cognitive Control

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(LACC), and temporal descriptions of human–machine interaction through the Score notation. Details of the Joint Control Framework can be found in (Lundberg & Johansson, 2021).

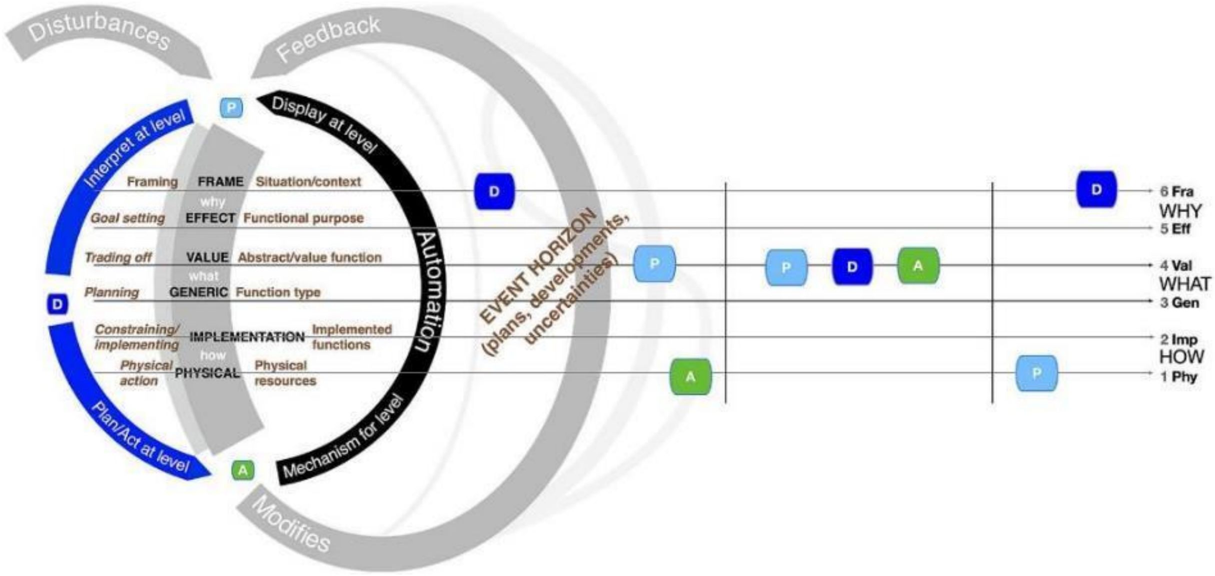

Figure 4: The Joint Control Framework (Lundberg & Johansson, 2021)

The 'PPP" Trust Model is almost 20 years old but deserves mention for its impact and longevity. Many of the current trust frameworks and measurement schemes incorporate Lee & See's (2004) idea that trust is calibrated through assessment of three aspects of agent behaviour: overt performance, underlying process, and the deeper purpose behind the agent. If there is one shortcoming of the PPP Model, and others that rely on it, it is that it focuses exclusively on dynamic or calibrated trust. That is, the model addresses how trust either develops or decays with the experience of interacting with automation.

The **MUFASA project** explored air traffic controllers' use of advanced decision aiding automation and put forward a theoretical framework for how to understand operators' decision to use or not use an intelligent aid. This view distinguishes factors both internal and external to the controller that feed into the evaluation decision. According to this model a cycle of use – feedback – assessment - trust recalibration occurs. This underscores one of the paradoxes of (optional use) intelligent aids: that an operator might only come to trust the system after using it but might not choose to use it until they trust it. Notice that this model also distinguishes three levels of trust, based on Lee and See's (2004) trust model. According to Lee and See, the only objective indication we get of another agent's performance (whether that agent is an intelligent aid, a robot, or another human) is their observable performance. Based on this we all infer underlying process and further, underlying purpose. Lee & See's widely accepted model of trust dimensions has been called the PPP Model.

In addition to 'calibrated trust' (via the PPP model), operator automation strategy is driven by a dispositional trust, that is a more general tendency to trust or distrust automation. It is often assumed (correctly or not) that dispositional trust toward new advanced technologies decreases with age. Finally, the interaction between external contextual factors and internal "performance shaping factors" drive the final decision of whether to rely on automation or not. Time pressure and task criticality, for example, can be important drivers of the use decision. This underscores the distinction between acceptance of and agreement with automation. If time is tight, the operator might accept the use of automation that they would not necessarily agree with.

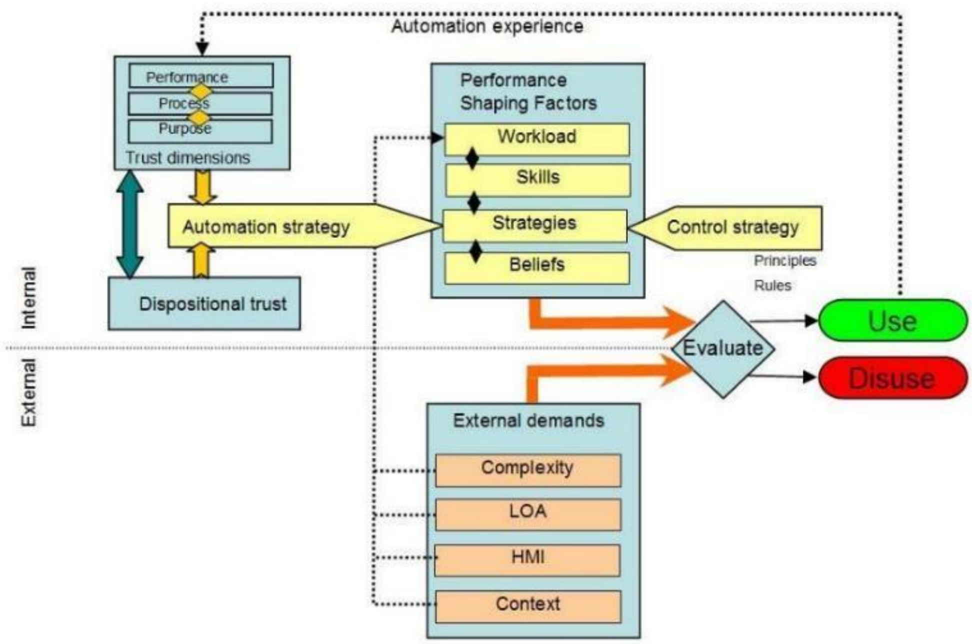

Figure 5: The MUFASA Automation Use Model (MAUM, after Westin & Hilburn, 2011)

Chen et al. (2018) developed the **"situation awareness-based agent transparency" (SAT)** model to explain human awareness of an agent's current actions and plans, reasoning process, and outcome predictions. The original SAT model (Chen et al., 2014) was expanded to incorporate teamwork and bidirectional transparency (Chen et al, 2018). The SAT model integrates a few widely accepted component models. First is Endsley's three stage model (perception, comprehension, projection) of situation awareness (Endsley, 1995). It is also built on Lee & See's (2004) PPP trust model and Rao & Georgeff's (1995) BDI (beliefs, desires, intentions) agent framework. In 2018, four years after their original SAT model, Chen and her colleagues acknowledged the increasing role of machine learning and 'mixed initiative' teaming and updated the SAT model by incorporating teamwork transparency and bidirectional communications aspects between human and agent.

Situation Awareness-based Agent Transparency

Level 1: Goals & Actions

Agent's current status/actions/plans

- Purpose: Desire (Goal selection)
- Process: Intentions (Planning/Execution); Progress
- Performance
- Perception (Environment/Teammates)

Level 2: Reasoning

Agent's reasoning process

- Reasoning process (Belief/Purpose)
- Motivations
  - Environmental & other constraints/affordances

Level 3: Projections

Agent's projections/predictions; uncertainty

- Projection of future outcomes
- Uncertainty and potential limitations; Likelihood of success/failure
- History of Performance

Figure 6: The original situation awareness-based agent transparency (SAT) model, adapted from Chen et al. (2014).

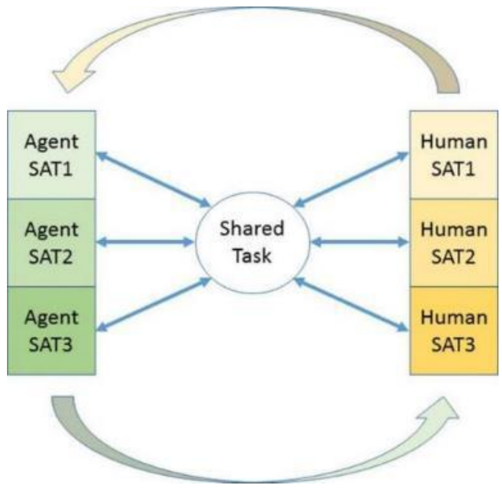

Figure 7: Revised SAT model (Chen et al., 2018) - model of bidirectional, situation awareness-based agent transparency in human–agent teams.

WP5 will use one of these methods (or a union of them) to structure the approach to adaptation strategy. Once unwanted mental states levels are predicted by the system, the strategy shall select a strategy able to avoid issues and maintain good human-ai teaming levels.

3.2.8 H-AI teaming and performance

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To date, multiple measures have been identified capable of assessing the performance of a team that involves human agents and AI systems such as individual cognitive process measures, teamwork measures, and outcome performance measures. The table below lists some relevant measures for the evaluation of Human-AI teams.

Team Performance

- Quality
  - Decision Making
  - Performance Outcomes
- Time on Task
- Operations Under Failure or Unanticipated Conditions
  - Recovery Time
  - Recovery Quality
  - Resilience
  - Bias Propagation
  - Adaptability
- Safety

Team Sustainability

- Human
  - Job Satisfaction
  - Skill Retention
- System
  - Maintainability & Auditability
  - Vulnerability
  - Suitability

Team Knowledge

- Situation Awareness (Models)
  - Team
  - Shared
- Mental Models
  - Team
  - Shared
- Knowledge
  - Teamwork
  - Taskwork

Team Processes

- Team Situation Awareness Processes
- Team Trust
- Team Distrust
- Teamwork Quality
  - Cohesion
  - Coordination
  - Cooperation
- Communications
- Behaviors

Team Efficiency

- Training Time
- Team Organization Optimality
  - Effectiveness of Resource Utilization
  - Mutual Performance Monitoring
  - Coordination Efficiency
  - Flexibility
  - Time to Resolve Uncertainty (TRU)
- Workload
- System
  - Usability
  - Understandability
  - Predictability
  - Controllability
  - Trustworthiness
  - Responsivity
  - Reliability
  - Robustness
  - Over-Promise Rate (OPR)
  - Bias

Figure 8: Human-AI team metrics (National Academies of Sciences, Engineering, and Medicine, 2022)

Cognitive process measures, including workload and situation awareness, have been extensively studied and validated in the context of human-automation interaction (e.g., Endsley and Kaber, 1999). These measures remain relevant for assessing the cognitive influence of human-AI teaming on human team members (Chen et al., 2018; Mercado et al., 2016).

Since **trust** can mediate the degree to which people rely on each other or on a technology such as AI (National Academies of Sciences, Engineering, and Medicine, 2022) several rating-scale measures of trust have been created, differing in the number and nature of items they include (Hoffman et al., 2018).

Due to the relevance of **mental models** in enhancing team performance, research has recently focused on evaluating people's mental models of AI systems to assess their understanding of those systems. To achieve this, various approaches have been developed including think-aloud protocols, question answering/structured interviews, self-explanation tasks, and prediction tasks that involve individuals predicting the actions of an AI system in different situations (refer to Hoffman et al., 2018 for more details). Research has also concentrated on explainability, resulting in the development of various types of metrics. These include a questionnaire designed to evaluate people's satisfaction with explanations, measuring how well they perceive their understanding of the AI system or process being explained (Hoffman, 2018), as well as a measure of explanation quality based on Endsley's (1995) Situation Awareness Global Assessment Technique, proposed by Sanneman and Shah (2020). In addition, teamwork process (e.g., communication, coordination, team situation assessment, team trust, and team resilience) measures employed in all-human teams have been modified for assessing teamwork in human-AI teams. While scales for self-assessment of team processes or observer assessment of team processes already exist (Entin & Entin, 2001), there is an emerging shift towards unobtrusive real or near-real-time measurements of teamwork (Cooke & Gorman, 2009; Gorman, Cooke, and Winner, 2006; Huang et al., 2020). Stevens et al. (2014) also proposed physiological measures of teamwork, including neural synchrony. Furthermore, another crucial set of measures for assessing human-AI teams relates to the objective performance on specific tasks, traditionally including the evaluation of quality of performance and completion time. Finally, a significant consideration when assessing the outcome performance of human-AI teams also involves evaluating the effectiveness of a human-AI team in unforeseen conditions, especially beyond the boundaries of the AI system, often in terms of out-of-the-loop recovery time (Endsley, 2017; Onnasch et al., 2014).

3.2.9 Tasks allocation between AI and Human

Out-of-the-loop (OOTL) performance issues can arise when humans experience low Situation Awareness (SA) while collaborating with automation. As stated in Endsley (2017), Endsley and Kiris (1995), and Wickens (2018) this can be attributed to several factors, including:

1. Challenges related to monitoring, vigilance, and trust.
2. Insufficient information feedback and limited transparency in automated systems.
3. Reduced human engagement when operating at higher Levels of Autonomy (LOAs).

The Level of Autonomy (LOA), also referred to as the degree of automation, is defined in terms of the ways portions of any given task can be allocated between the human and the automation or AI system (Endsley & Kaber, 1999; Kaber, 2018; Parasuraman et al., 2000; Sheridan et al., 1978). Adaptive AI agents add complexity to human-AI teams as human team members must adapt their interactions and information sharing to the agent's changing autonomy level. Effects of LOA on human workload, SA, and performance have been addressed by existing research (Endsley, 2018).

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	Effect of Autonomy Applied to Stage of Task Performance				
Taxonomy	**Situation Awareness**		**Decision**		**Action**
Kaber and Endsley (1997)	Monitoring Information		Option Generation	Action Selection	Implementation
Parasuraman, Sheridan, and Wickens (2000)	Information Filtering	Information Integration	Action Selection		Action Implementation
General Findings	Significant benefit to SA, workload, and performance from systems that present needed information (Level 1 SA) Significant benefit to SA, workload, and performance from systems that integrate information needed for comprehension (Level 2 SA) and projection (Level 3 SA) Better SA and little OOTL problem compared to decision automation		Significant benefits when system is correct Decreases performance when system is incorrect due to decision biasing Slower performance due to need to compare recommendations to system information and to other options Lowers SA and increases OOTL performance problems		Significant benefits to performance for routine, repetitive manual labor if reliable Manual workload may be lower overall Increases in cognitive workload at peak times Increases in workload for systems with high false alarm rates and low reliability
Task-specific Findings	Information cueing systems create good performance when correct but poor performance when incorrect, similar to decision-biasing effects. Information filtering systems can limit Level 3 SA (projection), negatively impacting performance		Automation of selection between alternatives less of a problem for performance than automation that generates options that affect engagement Decision support based on critiquing systems or what-if reasoning and contingency planning do not create decision biasing problem due to higher engagement		Lower SA and significant OOTL problems for automation that employs advanced queuing of tasks Lower SA and significant OOTL problems for automation of continuous-control tasks

NOTE: SA – situation awareness; OOTL – out of the loop.
SOURCE: Endsley, 2017, (p. 13). Reprinted with permission from Sage Publications.

Figure 9: Summary of Research on Effects of LOA and Human SA, Workload and performance.

However, McNeese et al. (2018) demonstrated that to fulfil a team role and operate in complex situations AI agents need to function with a relatively high level of autonomy.

3.2.10 Relevant regulations

The aviation and Air Traffic Management (ATM) sectors are witnessing a transformative shift with the integration of Artificial Intelligence (AI) technologies. These technologies offer the potential to enhance safety, efficiency, and decision-making processes in aviation operations. To ensure the responsible and effective use of AI in these critical domains, various aviation authorities and organizations have developed comprehensive guidelines and frameworks. Among these, the European Union Aviation Safety Agency (EASA) and EUROCONTROL play prominent roles in shaping the guidelines for AI adoption in aviation and ATM. Here, we review the guidelines introduced by EASA and EUROCONTROL.

The EASA (European Union Aviation Safety Agency) AI Trustworthiness Guidance is a significant initiative aimed at reliability of Artificial Intelligence (AI) systems used in aviation.

The EASA AI Trustworthiness Guidance is designed to establish guidelines and expectations for the trustworthy use of AI in aviation. Key points covered by this document include:

- **Trustworthiness:** The guidance focuses on ensuring the trustworthiness of AI systems, covering aspects such as safety, ethics, fairness, and reliability.
- **Concept of Operations (ConOps):** It includes a detailed concept of operations for AI applications to support compliance with trustworthiness guidelines. This ConOps helps in understanding how AI systems should operate safely and reliably.
- **Fairness:** The guidance emphasizes the need to establish mechanisms to ensure fairness in AI-based systems. This is crucial to prevent biases or discrimination in AI outcomes.
- **Transparency:** Transparency in AI operations is a key element. AI developers are encouraged to make AI systems transparent, allowing for better understanding and auditing of their decisions.
- **Early Visibility:** The guidance aims to provide early visibility to applicants regarding EASA's expectations concerning AI systems in aviation.
- **Regulatory Milestones:** It aligns with EASA's roadmap for AI, marking milestones in the development and certification of AI applications in aviation.
- **Webinars:** EASA has conducted webinars to communicate its progress and principles related to AI trustworthiness.

The EASA AI Trustworthiness Guidance serves as a framework to ensure that AI technologies are integrated into aviation safely, ethically, and with a strong focus on reliability and fairness. It plays a pivotal role in shaping the future of AI applications in the European aviation industry.

The EASA (European Union Aviation Safety Agency) **Artificial Intelligence Roadmap** represents a strategic approach to integrating artificial intelligence (AI) in aviation while maintaining a human-centric approach. Key points about the EASA Artificial Intelligence Roadmap include:

- **Human-Centric Approach:** The roadmap emphasizes a human-centric approach, which means that AI in aviation should be designed to assist and augment human activities, enhance safety, and optimize operations rather than replace human roles.
- **Safety and Trustworthiness:** Safety and trustworthiness are core principles. EASA aims to ensure that AI systems deployed in aviation meet rigorous safety standards and can be trusted to operate reliably.
- **Risk Management:** AI is seen as a key enabler for emerging risk detection and risk classification within EASA's safety intelligence and management domain. It can help identify potential safety issues early on.
- **Comprehensive Action Plan:** The roadmap provides a comprehensive action plan for the EASA AI Programme. It includes conceptual guidance deliverables and anticipated rulemaking activities, outlining the steps needed for the safe and trustworthy integration of AI in aviation.
- **Focus on Safety and Security:** The document underscores the importance of safety and security in AI adoption, highlighting EASA's commitment to ensuring that AI technologies don't compromise aviation safety or security.
- **Integration of AI:** EASA envisions the integration of AI in various aspects of aviation, such as air traffic management, maintenance, and safety monitoring. This integration is intended to enhance efficiency and overall aviation operations.
- **Version Updates:** The roadmap has evolved over time. The current version is the EASA Artificial Intelligence Roadmap 2.0, reflecting ongoing efforts to refine and enhance the approach to AI in aviation.

Overall, EASA's Artificial Intelligence Roadmap outlines a thoughtful and systematic strategy for adopting AI technologies in aviation, with a strong emphasis on safety, trustworthiness, and a human-centric perspective.

The "EASA Concept Paper: guidance for Level 1 & 2 machine learning applications" is a document published by the European Union Aviation Safety Agency (EASA) that provides guidance on the use of machine learning applications in aviation, specifically for Level 1 and Level 2 applications. Here's an overview:

- **Scope:** This concept paper focuses on machine learning applications in aviation, particularly those categorized as Level 1 and Level 2.
- **Level Classification:** Machine learning applications in aviation are typically categorized into different levels based on their criticality and impact on safety. Level 1 applications are considered to have a lower impact on safety, while Level 2 applications may have a higher impact.
- **Guidance:** The concept paper aims to provide guidance on the development, certification, and use of machine learning applications at these levels. It may include recommendations, best practices, and safety considerations.
- **Safety Assurance:** Ensuring the safety of machine learning applications in aviation is a paramount concern. The concept paper likely addresses safety assurance processes and methodologies specific to these applications.
- **Certification:** Machine learning applications used in aviation often need to go through a certification process to ensure they meet safety standards. The concept paper may outline certification requirements and procedures.
- **Human Augmentation:** It's worth noting that Level 1 and Level 2 machine learning applications may involve human augmentation, where AI systems assist human operators rather than replace them. The concept paper may address this aspect.

Revision and Refinement: The concept paper is subject to revision and refinement as the field of machine learning and aviation evolves. New versions of the paper may be issued to incorporate updated guidance and standards. In summary, the EASA Concept Paper provides essential guidance for the safe and effective use of machine learning applications in aviation, focusing on Level 1 and Level 2 applications and emphasizing safety and certification processes.

The EASA (European Union Aviation Safety Agency) Artificial Intelligence Roadmap 2.0 is a comprehensive plan that outlines the Agency's vision for the safe and ethical integration of artificial intelligence (AI) in aviation. Here are the key points regarding the AI Roadmap 2.0:

- **Focus on Safety and Trustworthiness:** The roadmap places a significant emphasis on ensuring the safety and trustworthiness of AI applications in aviation. It addresses the critical importance of AI systems being reliable and secure.
- **Ethical Considerations:** In addition to safety, ethical considerations are a fundamental aspect of the roadmap. It aims to ensure that AI in aviation adheres to ethical standards and respects human values and rights.
- **Living Document:** The EASA AI Roadmap 2.0 is treated as a "living document." This means that it is subject to regular updates and revisions to keep pace with the rapidly evolving field of AI technology and its applications in aviation.
- **High-Level Objectives:** The roadmap sets high-level objectives and actions to guide the integration of AI into aviation effectively. These objectives likely encompass areas such as risk management, certification, and human-machine collaboration.

- **Trustworthiness of AI:** EASA places a strong emphasis on building trust in AI systems. This involves creating robust processes for AI system certification, ensuring transparency, and developing mechanisms for risk assessment and management.
- **Annual Amendments:** EASA commits to amending the roadmap annually. This reflects the dynamic nature of AI technology and the need for continuous adaptation to new developments and challenges.
- **Collaboration:** Given the complexity of AI in aviation, the roadmap likely encourages collaboration between stakeholders, including regulatory bodies, industry players, and AI developers, to achieve the stated goals.

In summary, the EASA AI Roadmap 2.0 is a forward-looking document that guides the safe, ethical, and trustworthy integration of artificial intelligence into the aviation sector. It prioritizes safety, transparency, and collaboration to ensure that AI enhances aviation operations while maintaining the highest standards of reliability and security.

Finally, also the following regulations will be considered:

- Commission Regulation (EU) 2015/340 of 20 February 2015 laying down technical requirements and administrative procedures relating to air traffic controllers' licences and certificates
- Commission Implementing Regulation (EU) 2017/373 of 1 March 2017 laying down common requirements for providers of air traffic management/air navigation services and other air traffic management network functions and their oversight

EUROCONTROL is fully committed to support the acceleration of AI adoption in European aviation, and more specifically in air traffic management, through the following actions:

- The FLY AI initiative, a coordinated action of European aviation/ATM actors to demystify and accelerate the uptake of AI (see below);
- Support to EUROCAE and EASA for the development of AI standards and guidelines for aviation/ATM;
- The development of AI trainings and webinars;
- The development of AI-based ATM applications notably through research and innovation actions together with a suitable data and AI infrastructure framework;
- The deployment of AI-based ATM applications at Network Level to be used by the whole aviation.

The FLY AI Action Plan is a significant initiative developed by EUROCONTROL in collaboration with its partners to promote the use of artificial intelligence (AI) in aviation and air traffic management (ATM). This action plan is outlined in the "FLY AI Report" and serves as a roadmap to advance the integration of AI technologies in the aviation industry. Key points about the FLY AI Action Plan include:

- **Practical Recommendations:** The FLY AI Action Plan provides a series of practical recommendations aimed at driving AI forward in the aviation sector. These recommendations are designed to address the challenges and opportunities associated with AI adoption.
- **Federated AI:** One of the notable recommendations in the action plan is the creation of a federated AI approach. This approach encourages collaboration among various stakeholders in the aviation community to collectively harness the potential of AI.
- **Integration in ATM:** The FLY AI Action Plan emphasizes the importance of integrating AI technology not only in aviation operations but also in air traffic management (ATM). It outlines

measures to better incorporate AI in various segments of ATM to enhance efficiency and safety.

- **Future Measures:** The action plan goes beyond the current use of AI and outlines future measures to advance AI's role in aviation. It envisions a more AI-centric approach in the industry's operations and decision-making processes.
- **Industry Impact:** The FLY AI Action Plan has the potential to significantly impact the aviation industry by making it more efficient, data-driven, and technologically advanced.

Overall, the FLY AI Action Plan is a forward-looking initiative that seeks to demystify AI and accelerate its adoption in aviation and ATM. It reflects the commitment of EUROCONTROL and its partners to embrace AI as a transformative technology in the aviation sector.

3.3 State of the art for mental states prediction

As anticipated in the previous paragraphs, anticipating operators' mental states is a fundamental step for providing an effective Human-AI teaming.

3.3.1 States, attentional tasks, and processing phases

We must distinguish between Mental States, attentional tasks and processing phases. A mental state is a mental condition in which a person finds themself because of the state of the mental resources that they use to perform a task. Mental resources within the human energetic paradigm can be understood as an amount of energy. Within this context mental resources management is presented as an adaptative mechanism that addresses the energy demanded to perform tasks (demanded resources), the available energy in each moment (available resources) and the energy the human is willing to apply to perform the tasks (applied resources).

Mental states are presented in this section as the different relationship or management of these mental resources.

The mental state that we call Mental Workload is the mental condition that results from the relationship between the mental resources that the task demands to be performed optimally and the mental resources that the person has available to perform it.

The mental state that we call Fatigue is the mental condition in which a person finds themself because of the number of mental resources they have available at a given moment.

The mental state we call Stress is the condition in which a person finds themself when they must activate mental resources to face a threat.

An attentional task is a task in which performance depends fundamentally on attentional processes. An example of an attentional task is the Vigilance Task, which is a task in which a person must attend to a sector of the environment to detect the appearance of a stimulus. A vigilance task is performed, for example, by a person who must attend to radar to detect the appearance of an airplane.

A cognitive function or processing phase is a stage in the mental processing of information in the environment. What we know as "Situation Awareness" is a sequence of three stages in information processing: the perception of the elements of the environment, the understanding of its current situation and the projection of its future situation.

Mental states, attentional tasks, and processing phases are conceptually different, although related. For example, mental states affect performance on the vigilance task and situation awareness. Similarly, the processing phases of situation awareness are involved in the vigilance task. However, it is convenient that we know how to distinguish between these three psychological concepts.

<table>
<tr><th>Mental States</th><th colspan="2">Cognitive Functions</th><th>Tasks</th></tr>
<tr><td></td><td colspan="2">Attention</td><td rowspan="2">Attentional and Vigilance</td></tr>
<tr><td rowspan="3">Workload
Fatigue
Stress</td><td rowspan="2">Situational Awareness</td><td>Perception</td></tr>
<tr><td>Comprehending
Projecting</td><td>Evaluating</td></tr>
<tr><td colspan="2">Decision Making</td><td>(Re)Planning</td></tr>
<tr><td></td><td colspan="3">Implementing</td></tr>
</table>

Figure 10: Mental states, related cognitive functions and tasks

3.3.2 Mental states

3.3.2.1 Workload

The number of mental resources that are applied to perform a task depends on the resources that the task demands and the resources that the person has available. The resources that the task demands depend fundamentally on its complexity, and the resources available to the person rely on a series of factors that determine the level of psychophysiological activation (sleep, circadian factors, etc.).

We call mental load the discrepancy between the resources demanded by the task and the available resources the person has. When the resources required are many, many more than the available resources, we speak of "Mental overload", and when the resources demanded are less than those available, we speak of "mental underload."

In Human Factors and Ergonomics, it has been demonstrated for a long time that both mental overload and underload harm the performance of tasks and for that reason, in the research and professional practice of specialists in Ergonomics and Human Factors Mental Workload is a fundamental factor when analysing work.

What predicts mental workload and should be considered when developing a model?

- **Relationship between taskload and workload**

  In the scientific literature on Human Factors and Ergonomics it is also common to talk about Taskload. However, it is necessary to distinguish the two terms, Taskload and Workload. Taskload are the resources demanded by the task while Workload is the relationship between the demanded resources (taskload) and the available resources. Therefore, Taskload is only a measure of the demanded resources calculated from the characteristics of the environment. In CODA, task prediction models will support the identification of demanded resources.

- **Cognitive complexity and workload**

  The resources demanded by a task depend on the cognitive complexity of that task. It is important to keep in mind that complexity does not depend only on the characteristics of the task but on how these characteristics are cognitively processed by the person who is executing it. Therefore, we might say that when we measure the resources demanded by a task, we are measuring the Cognitive complexity of that task as measured by calculating the mental processing of the characteristics of the task and the environment in which that task is performed.

- **Available resources and workload**

  Generally, the resources available at a given time depend on three factors. On the one hand, there are individual differences that determine whether a person has more or fewer resources available to perform a task. Secondly, depending on the specific moment we measure them, we will observe that a person has more or fewer resources available. We know, for example, that there are people who have more resources in the morning and less in the afternoon. In the same way, on Mondays, after a weekend of rest, you have more resources than at the end of an intense work week. Finally, the ingestion of certain substances can modify the amount of resources available. For example, after ingesting certain foods or certain medications (painkillers), the amount of mental resources can be reduced. These three factors determine the level of psychophysiological activation that is responsible for the number of available resources that a person has at a given moment.

  However, it is also necessary to consider that there are external factors (for example, a threat or danger) that can cause mental states that activate psychophysiological responses, increasing the level of available resources, as is the case with what happens with stress.

  In any case, when talking about available resources, it is necessary to say that these resources are limited and could be exhausted. We could say that it is not possible for any person to have unlimited resources for an unlimited time. For this reason, we must talk about Fatigue, which is a mental state defined by the exhaustion of available resources.

A model for controller workload has been proposed in e-Commet, that takes into account the available and demanded mental resources. (de Frutos, et al., 2019).

As presented in section 3.1.1 Workload, this mental state can be measured using EEG measurements, which should correspond to the model developed within CODA regarding mental resources available and demanded.

3.3.2.2 Mental fatigue

Mental fatigue is conceptualized as the exhaustion of cognitive resources that a person experiences while performing a task. At the initiation of a task, a person has limited resources available that will have to use to perform it. If these resources are not enough for the execution of the task and they are not replaced, the resources will be exhausted, which will produce the phenomenon known as mental fatigue. Mental fatigue expresses itself as a subjective feeling of tiredness and as a worsening in the performance of the task and, therefore, in the quality and quantity of work performed.

Despite the previous statement, the task execution may not be affected due to the provision of extra resources from a compensatory mechanism that fosters arousal and alertness, known as the "Ascending Reticular Activating System" or ARAS. Together with this enabling mechanism, there is an inhibition mechanism that indicates that the metal resources are exhausted and must be replaced. This mechanism is the responsible of the subjective feeling of tiredness. Some of these mental mechanisms can be measured using the different methods proposed in 3.1.4 Mental fatigue (EEG, EOG,…).

What predicts (affects) mental fatigue and should be considered when developing a model?

- **Time-on task:** The time-on task (or shift length) is considered as one of the effective ways to prevent fatigue in Air Traffic Control. ANSPs acknowledge this by establishing not only the length of shifts but also the number of breaks and their duration that are associated with the workload. As example, United Kingdom ATCos Regulations established: no operational duty shall exceed a period of two hours without there being taken, during or at the end of that period, a break or breaks totalling no less than 30 minutes; — during periods of high traffic density, the possibility of having more frequent short breaks (ten minutes) should be provided.

  Hockey (2013) proposed a functional relation between task execution and time-on-task which has three phases. At the beginning of the task, there is a decrease or "Habituation" where the function exponentially decreases. Next, the body resists fatigue by making an extra effort that keeps the performance stable for a while. Finally, it may be that the effort to keep execution at an optimal level is excessive and a "disengagement" of the task occurs to devote efforts to seeking a new strategy to execute it (seeking new objectives, etc.)

  This can be modelled as a function where the operation method of a person changes to compensate for the reduction of mental resources available.

- **Sleep:** The circadian factors related to the number of hours that a person has been awake influences the available mental resources. Nevertheless, for this project we will assume that mental resources are available when tasks are initialized, and the impact of sleep will not be modelled.

- **Workload:** Another important factor on mental fatigue is the intensity of a task or workload. The complexity and resources necessary to perform a task produces that the mental fatigue appears earlier or later in time.

  As previously presented, the impact of workload can be modelled as the demand of metal resources against the available ones.

- **Shiftwork:** Studies regarding controllers and mental fatigue indicate that shift work has a clear influence. The studies indicate that there are significant differences between day/night shifts, time periods, shift start time, before break time, after break time, and shift end time), and various work schedules. Again, for this project we will assume that the mental resources are available when tasks are initialized, and the impact of shift work will not be modelled.

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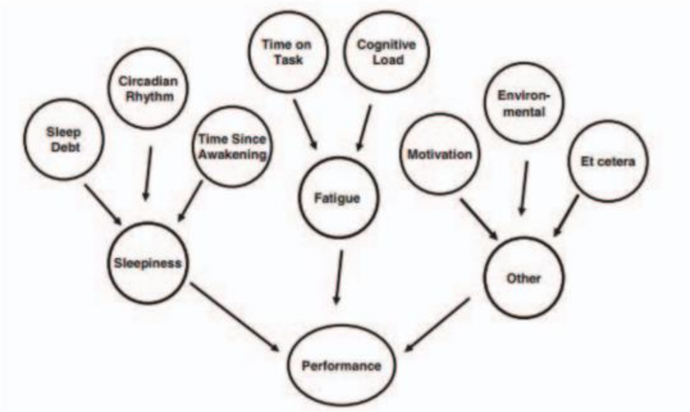

Figure 11: Conceptualisation of a set of factors that influence human performance and fatigue (Balkin, 2011)

3.3.2.3 Stress

Unlike fatigue, which is an effect of resource depletion over time, stress is mental state that evolution has created to provide resources to the organism increasing their available resources. From this point of view, we can define this mechanism as responsible for a general response of the organism to any stimulus or threatening situation that we call stressor or stressful factors (Selye, 1956).

The most accepted contemporary model is the transactional model of Lazarus (Lazarus & Folkman, 1984) that states that the stress is a result of a transaction between a person and the environment. When the environment demands exceed the individual resources available, the level of stress is higher. Stress is thus influenced by external objective factors (e.g. noise) and cognitive factors that vary from one individual to another (e.g. level of difficulty of a task). Stress can interfere with performance. Stress is characterized by a set of body alterations that include among other indicators blood pressure, cortisol, skin conductance and heart rate variability among others (see 3.1.2 Stress for further details).

3.3.3 Cognitive Functions and tasks

Cognitive functions are cognitive processes responsible for processing information from the environment and behaving to modify that environment.

3.3.3.1 Attentional tasks

Attention is extracting from the mind, in a clear and vivid way, one item among several possible objects appearing simultaneously. Targeting, concentration and consciousness constitute its essence. It involves leaving certain things to deal with effectively others. There are several characteristics of attentional tasks,

- Selective attention, where a person selects the prioritization of a task or scanning of the environment,
- Focused attention, where a person keeps attention to a task or sector of the environment without distractions, nonrelevant events or competing tasks diverting it.
- Divided attention, where two tasks are performed simultaneously (switching from one to another in seconds).

- Maintained attention, where attention must be kept during a large amount of time (vigilance).

Attentional tasks can be modelled as a management of mental resources that varies with the type of attentional task being performed.

Selective tasks can use the SEEV model, salience, effort, expectancy, value, developed by Wickens et al. (2009). The model indicates that our attention is captured by the most salient stimuli, by the expectations about where they may appear, by the effort to inhibit the stimuli that distract us, and by the value of the information that gives us the stimuli.

In divided attention the demand of mental resources may overlap in time, increasing the total demand when compared to the one needed if each task is performed individually (Wickens et al., 2009).

Vigilance can be modelled as a task that demands high mental resources that degrades rapidly with time.

3.3.3.2 Situational awareness (cognitive function)

Situational awareness, SA, can be defined as the ability to perceive the environment, understand it, and predict its future. This definition related to information processing has a three steps model (Endsley, 1995). This model follows a chain of information processing, from perception, through interpretation, to prediction.

- *Level 1: Feel and Perception of the elements in the environment.* It is related to the acquisition of information and no processing is performed at this stage. A stimulus must be above a perceptual threshold to be registered by the individual. Signal detection theory supports the modelling of this step.

- *Level 2: Comprehension of the current situation.* It is the creation of a mental representation of the current situation. This metal representation is created in the working memory by combining information that is being perceived with information that is stored in long-term memory. Mental abstractions are used to perform this understanding. A model for air traffic controller abstraction was proposed by Histon, .

- *Level 3: Prediction of future status.* It is the ability to project the future of the elements in the environment, this means the prediction of the future state and behaviour of a system. Several cognitive projection processes have been proposed in the ATC world. In general, two factors have been identified as impacting ATC projection:

    - General cognitive processes. There are two models backed by experimental results. The cognitive model of extrapolation of movement where the observer develops a mental model of the movement of the object. The cognitive clock model, where the observer estimates a visual contact time (TTC) and then uses an internal clock mechanism to count up to that TTC.

    - Projection based on ATC knowledge. This process can be improved by training and support tools that take into account the ATC relationship with the environment (Degas et al., 2022)

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There is a close relationship between mental workload and SA. In each of the processing phases that make up SA, it is necessary to apply mental resources. Therefore, the efficiency of perceiving, understanding and projecting will depend on the complexity of the processing in these phases and the resources that the person has available.

3.3.3.3 Human Machine Performance Envelope

Feeding the cognitive model with the current ATCos mental states, estimated through their neurophysiological signals, we will be able to define the Human Machine Performance Envelope (HMPE) index. The HMPE index provides information on **how well the ATCo and the system are cooperating** (e.g., how promptly the ATCo is reacting to the different events) and it is able to predict the future operator status, hence assessing the Human-AI teaming quality/level.

3.4 State of the art for operators' state assessment (BS)

One crucial enabler for achieving effective human-AI teaming is to provide the AI system with some information related to the state of the operator interacting with Digital Assistants. On one side, the operator must maintain awareness of the system's status to spot deviations from expected behaviours and understand how the system works. On the other side, in systems in which automation is more and more suggesting solutions and making decisions, it is essential that the AI-based assistants have some information on the teammate they are collaborating with: Do they understand what is happening? Is this the right moment to provide information? Do they need some help now?

The mental states model based on mental resources must correspond to the evidence regarding the operator state provided by the physical measures. Neurophysiological measures can be employed to assess, even online, the mental states of the operator to enable the system to know their current levels of human factors during the execution of the operational task.

At the design level, this information can also be used to validate predicted cognitive models, maximising the effectiveness of the interaction between the human and the machine (see section 3.3).

The following paragraph will report how neurophysiological measures can be employed to provide information regarding the mental and emotional states of the user, in particular regarding Workload, Stress, Attention and Mental Fatigue.

3.4.1 Workload

Various mental workload definitions have been given during the last decades, showing that workload is a complex construct resulting from different interacting cognitive aspects. Mental workload measurement quantifies mental activity resulting from performing a task which takes into account the available and demanded resources.

Several empirical investigations have indicated that performance declines at the extremes of the workload demand continuum - that is, when the event rate is excessively high or extremely low. For these reasons, the mental workload is an essential and central construct in ergonomics and human factor research.

Moreover, the subjective measures of workload perception could be performed through several questionnaires, such as the NASA-TLX. Because of their inherently subjective nature, questionnaires do not allow for an objective and reliable measure of the actual cognitive demand in a real environment. Therefore, it has already been demonstrated in several contexts that the assessment of mental workload by electroencephalography (EEG) provides the sought-after reliable and objective measure (Aricò et al., 2016a; Aricò et al., 2016b).

This evidence showed that the brain electrical activities fundamental for the mental workload evaluation are the theta and alpha EEG rhythms on the Pre-Frontal Cortex (PFC) and the Posterior Parietal Cortex (PPC) regions. The theta rhythm, especially over the PFC, presents a positive correlation - i.e. increases when the mental workload increases (Borghini et al., 2013), while the alpha rhythm, especially over the PPC, presents an inverse correlation - i.e. decreases (Gevins et al., 1997). In recent studies (Borghini et al., 2015), it has been demonstrated how it was possible to compute, by machine learning techniques and specific brain features, an EEG-based Workload Index able to significantly discriminate the workload demands during realistic tasks.

3.4.2 Stress

Stress is typically defined as a state that occurs when demand outstrips coping strategies (Hobfoll & Shirom, 1993). In a realistic context, it is easy to meet stressful factors as high task demand, uncontrollability, frustration and time pressure, and such stressors negatively influence performance, altering cognitive processes at the base of decision-making, attention and memory. Laboratory studies have been largely adopted to study correlates of stress using tasks and protocols that are proven to induce stress in a controlled way. According to the literature (Skoluda et al., 2015), one of the most effective stressors is exposing a participant to a negative judgment. In fact, when negative feedback is provided to the participant, stressful sensations based on frustration will cause time pressure and make the task harder. Following this indication, we adopted three different stressors during this experimentation:

- Increasing difficulty for tasks
- White Coat stressor to elicit social stress
- Noise as physical stressor.

Classical biochemical markers for stress are cortisol and epinephrine, which will increase rapidly with stress exposure. However, it isn't easy to measure the human cortisol level continuously and without interfering with the activities performed by the participant.

In this sense, a gold standard among the non-invasive measures of stress level is the analysis of skin conductance. In fact, when an individual is under mental stress, sweat gland activity is activated, thus reflecting in the skin conductance increasing. Since the sweat glands are also controlled by the Sympathetic Nervous System (SNS), skin conductance acts as an indicator for sympathetic activation due to the stress reaction. In general, it has been widely demonstrated that Skin Conductance, in both its two components, the Skin Conductance Level (SCR) and Response (SCR), increases as the stress increases.

Finally, the EEG stress assessment is possible thanks to its high temporal resolution and the possibility of direct access to Central Nervous System (CNS) activity (Borghini et al., 2020). From this point of view, it has been assessed that in the presence of stressors, there is decreasing alpha power in the prefrontal cortex and an increase in beta in temporal and parietal sites (Choi et al., 2015; Al-Shargie et al., 2016). Moreover, a correlation between cortisol and beta EEG band has been found (Seo & Lee, 2010). In different contexts, it has been proved that stress condition-induced brain activations asymmetry (Murat et al., 2009): it has been demonstrated that the right brain hemisphere is mainly involved in cortisol production than the left hemisphere (Lewis et al., 2007).

Concerning the previous project STRESS (GA699381), in which a comprehensive assessment of the stress state from a neurophysiological point of view was provided, the CODA project will employ a lighter version of the Stress neurophysiological index by using just a few EEG sensors in the parietal part of the head (Sciaraffa et al., 2022). This will have a clear impact on the future use of this technology in the ATM field, in which biosignal technology must be minimally invasive to be accepted and employed in the operational field (Refer to section 3.2.5 for more details on the STRESS project).

3.4.3 Vigilance

The Vigilance concept belongs to the broader attention domain, embracing the aspects related to the activation. The task execution with an optimal level of performance is possible because, for the entire duration of the task, there is an appropriate level of activation managing resources involved in information processing (Parasuraman et al., 1998). Therefore, a physiological vigilance decrement during time is associated with a performance decrement. From the neurophysiological point of view, it has been already demonstrated that vigilance-related processes involve mainly the right inferior frontal brain regions (Di Flumeri et al., 2019; Sebastiani et al., 2020; Sciaraffa et al., 2021). Using ad-hoc monotonous tasks to analyse vigilance increased frontal beta activity more in the right than in the left hemisphere, suggesting a decrement of vigilance (Molina et al., 2013).

A neurophysiological measure of the Vigilance index has already been validated during the MINIMA project. Anyhow, in the CODA project, a lighter version of this index, by using just frontal EEG electrodes located in the right hemisphere, will be used (Sciaraffa et al., 2022).

3.4.4 Mental fatigue

Fatigue can be defined as a feeling of tiredness and exhaustion (Al-Shargie, 2016). In general, the presentation and symptoms of fatigue are not specific. Physical, physiological, and psychological factors all have the potential to create fatigue. There are several physiological measures to monitor fatigue, and the most used are EEG, Electrooculography (EOG), Electrocardiography (ECG), Photoplethysmography (PPG), and Electrodermal Activity (EDA). Regarding EEG, there is broad agreement about the fact that frequency rhythms indicate a level of a fatigued state, even if some studies focused on Alpha rhythm (Fujiwara et al., 2018; Di Flumeri et al., 2022), while others investigated Theta and Delta (Nguyen et al., 2017; Arefnezhad et al. 2022). EOG monitors eye behaviour, and it can be estimated from an EEG signal. This approach reduces the invasiveness of EOG monitored by placing dedicated electrodes while keeping the information suitable for evaluating the physiological parameters relevant to fatigue. Several studies report increased eyeblink rate (EBR) and eyeblink duration (EBD) with fatigue. Contrarily, eyeblink amplitude (EBA) is found to decrease. The measures obtained with this approach are the same as the video-based measures. Another source of information regarding drivers' states is represented by the analysis of parameters estimated from the autonomic response. In particular, ECG and PPG signals, related to heart activity, and EDA, related to skin sweating, are relatively easy to record, and they can bring relevant information about the fatigued state. Heart Rate (HR) is one of the most common features extracted from ECG, and it represents the number of heartbeats in a temporal unit. The variation over time of the distance between two heartbeats, namely Heart Rate Variability (HRV), has been demonstrated to be correlated with the state of drowsiness, and it was found to decrease sleepiness and fatigue compared to alertness condition (Fujiwara et al., 2019). From the EDA signal, it is possible to extract two features, the Skin Conductance Level (SCL) and the Skin Conductance Response (SCR), that were found to be correlated with users' mental fatigue levels. The research on these parameters is more immature than the previous ones. However, there are some findings about a possible relation between skin conductance variations and mental fatigue (Bundele et al., 2009).

A more specific definition for the different mental states and how we are going to measure them within the project will be provided in **D3.2 Mental states prediction model.**

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3.5 State of the art for tasks prediction models

3.5.1 Introduction

If neurophysiological assessment can give information on the current state of operators to improve the interaction between humans and AI-based systems, the next step would be to be able to predict the future mental states to intervene in advance and avoid unwanted situations (e.g. high workload peaks) that can immediately impact performance and be hard to recover. The first thing to do to achieve this is to anticipate which tasks will need to be executed by the operator in the future.

Air traffic controllers (ATCos) play a crucial role in maintaining the safe, orderly, and efficient flow of air traffic while maintaining effective communication with pilots to ensure compliance with aviation regulations. These professionals serve in roles such as tower, en-route, area, approach, oceanic and terminal radar Controllers. They have various duties and responsibilities, such as communication, traffic management, safety assurance, emergency response, navigational assistance, documentation, training, and ongoing professional development. The working environment of an air traffic controller is often fast-paced, dynamic, and highly demanding. Controllers must remain focused and attentive to the multiple screens, radar displays, and communication systems in their workspace. They work in a highly structured and regulated environment, following specific procedures and protocols to ensure the safe and efficient movement of aircraft.

This section describes approaches for measurement, forecasting and prediction of controller tasks in this high-risk environment. Additionally, it mentions the challenges and limitations faced by task prediction, such as the dynamic nature of air traffic, and the requirements any method aimed for this must meet, including data security and privacy and real-time technological infrastructure.

Air traffic controllers are an integral part of the aviation industry, providing support and supervision throughout the flight's journey, from take-off to landing. Their multi-faceted role includes critical responsibilities such as air traffic clearance, contact procedures, instrument and missed approaches, vectoring, safety warnings, speed adjustments and traffic advisories, all with their associated tasks. All these tasks include the meticulous confirmation of pilots' readings and monitoring of related manoeuvres, ensuring that vital instructions on altitude, course and other parameters are followed accurately.

ATCos also perform other tasks, such as maintaining constant vigilance, ready to address any potential disruptions or delays affecting the aircraft's trajectory. When pilots request, controllers provide vector guidance to avoid observed traffic, thereby enhancing the safety of the airspace. Their commitment to tracking and relaying critical traffic information continues until the aircraft lands safely or moves to the warning frequency.

When operating within a high-stakes environment, security and efficiency are paramount, as described in (Maynard, 2021). Prediction models are crucial in identifying potential incidents or issues in advance, enabling ATCos to take proactive measures to prevent risks, minimize damage, and enhance security. Additionally, anticipating future requirements allows ANSPs to allocate resources more efficiently, leading to cost reductions. Task prediction further aids in process optimization, error reduction, and the assurance of high levels of quality and efficiency.

3.5.2 Methods for ATCo Task Prediction

The SoA related to ATCo Task prediction will be analysed below.

3.5.2.1 Historical Data Analysis

Analysing historical air traffic patterns is an essential tool for efficient and safe airspace management. This process involves the collection and study of data on past flights, including routes, schedules, aircraft types, weather conditions and congestion. This enables aviation authorities to forecast future traffic demand, optimize routes, plan airport expansions, proactively manage congestion, allocate resources efficiently and manage airspace safely.

A key concept here is traffic complexity, with many attempts to define, measure and predict it from historical flight analysis. For instance, the early paper (Chatterji, 2001) presented sixteen complexity measures describing air traffic patterns. Other classical and modern attempts to study this problem can be found in (Delahaye, 2000), (Isufaj, 2021), etc.

With a much higher granularity, the paper (D. Karikawa 2013) presents the COMPAS (Cognitive system Model for Simulating Projection-based behaviours of Air traffic controllers in dynamic Situations) system, which allows automatic ATCo task identification and visualization tools based on cognitive system simulation of an ATCos.

Of particular interest for CODA is the existence of the CRIDA data warehouse, which has stored historical data since 2018 on flight plans, radar tracks, sector configurations and ATC activity of ENAIRE. To define ATCo activity, a system like COMPAS is in place in the CRIDA data warehouse. This system can detect ATCo actions (in the form of events) automatically. This ATC activity, in the form of tasks being executed, will be used both as an input to the CODA ATC task prediction system (in the form of previous and current tasks being performed) and as the label for the supervised training (for future tasks, structured as a plan).

Some previous projects related to historical data analysis and task/complexity analysis are summarised in section 3.3.4 below.

In summary, by knowing past traffic trends, authorities can anticipate peak periods and allocate resources, ensuring that airports and air traffic control centres can cope with traffic peaks. Historical data informs infrastructure decisions, ensuring that airports can accommodate future growth without compromising safety. In other words, analysing historical air traffic patterns provides critical insights for authorities to anticipate and prepare for impending tasks, ultimately enhancing airspace management efficiency and safety benefiting both the aviation industry and passengers. In general, this analysis is performed at the strategic level, not in real-time; this idea of complexity may also be relevant for real-time task prediction, as we will see.

3.5.2.2 Real time ATCo Workload Prediction

Predicting the workload levels of controllers can be considered a pattern recognition problem and is, therefore, suitable for data-driven learning algorithms. To this aim, there are several potential strategies. The first is to link workload with the traffic situation directly.

This is the approach followed, for instance, by the paper mentioned in the previous section (Chatterji, 2001), which linked the complexity measures with the air traffic workload using a neural network. The same approach was also followed by (Pang, 2023). In this work, the problem of predicting workload based on the spatio-temporal layout of the airspace is considered a dynamically evolving time series graph classification task. In this study, it is proposed to introduce multiple historical graphs into the model to predict the workload level at the next time stamp. Moreover, the spatiotemporal layout of the graph structure varies at each timestamp (i.e., the number of nodes and the connections of the graph edges), giving rise to a dynamic graph classification problem. The paper also presents a dynamic density model, building a regression model to find linear relationships between traffic complexity factors and ATCo workload. However, dynamic density metrics do not consider human cognitive capabilities, the primary source of real-world ATCo workload sources.

Related to the link between complexity and ATCo Load, the paper (Cano, 2007) presents a methodology to analyse and react to the expected traffic flows that will take advantage of its more predictive ATM network. The paper describes eTLM (Enhanced Traffic Load Monitoring), which aims to react to traffic complexity by dynamically adjusting the sector configurations to real traffic situations.

3.5.2.3 Real Time ATCo Tasks Prediction

An alternative to direct workload derivation from traffic advocated in the CODA project is first to identify controllers' tasks. This has the additional advantage of enabling task distribution in the AI-human team. Next, we will focus on previous attempts to monitor/predict the controllers' tasks/actions.

The paper (Pham, 2020) describes a prediction model derived through supervised learning, where the target variables are planning controller actions (including altitude, speed and course changes), while the inputs have been ADS-B data (aircraft 4D trajectory) and sector information. The system automatically derived the sector entry and existing points and identified the needed ATCo interventions with reasonable accuracy (99% for vertical manoeuvres, 80-90% for horizontal actions).

In (Bastas, 2022), a Deep Learning approach is used to model actions related to conflict detection and resolution. It covers both the prediction of the time of the intervention and the type of resolution. For us, this approach is critical, as in our problem (as in the one addressed in the paper), it is not only essential to know what action will need to be performed but also when.

In any case, it should be emphasized that the previous literature focuses on actions related to conflict resolution. At the same time, our needs are more extensive, as we need to incorporate other types of tasks related to vigilance, routine communications, etc.

3.5.3 Challenges and limitations

ATCo task prediction has many different potential difficulties and limitations. Some of them will be summarised below:

1. Traffic uncertainty: There are multiple unpredictable elements that, during the different stages of flight, can produce unexpected changes in flight plans, even in the short term, such as atmospheric conditions derived modifications (especially with turbulent weather), conflict-induced modifications, onboard emergencies, etc.
2. ATCo task execution variability: although ATM is heavily regulated, and the types of tasks and typical interventions are clearly identified, different ATCos may perform different actions, and the order of their execution may change.
3. Constraints on data security and privacy: To be able to predict ATCo tasks, lots of operational data (at least sector definitions, flow definitions, recorded flight plans, recorded tracks, and ATCo actions) will need to be accessed to. Some of them may have security/privacy problems, which must be solved.
4. Scalability, the system's capability to handle large data volumes, must be guaranteed to maintain effectiveness and accommodate growth.

3.6 State of the art for adaptive systems (NLR + ENAC)

The term “adaptation” refers to a process where ATC system adapts its behaviour to individual users based on information acquired about its user(s) and its environment. In this context, the adaption can be based on:

- The current or predicted task for the controller;
- The current or predicted traffic situation; or
- The current or predicted state of the controller.

The adaptive system monitors the task of the controller, the traffic situation and/or the state of the controller in terms of workload, vigilance, fatigue and stress and combines the different sources of information (i.e. the human machine performance envelop – HMPE) to make a prediction of the future state.

Currently, there exist only a few examples in which the systems could be referred to as adaptive based on the controller’s task or the traffic situation. An example of a simple adaptive system based on the task of the controller is the Touch Input Device (TID). The controller uses the TID to make inputs to the ATC system based on updated information of the pilot/aircraft, updated flight plan information, or instructions given the controller. Depending on the selected option (by selecting a button), the TID displays only the relevant sub-choices (by showing buttons with different functionality) to the controller, see Figure 1. Hence, the controller is guided through the system options based on the task at hand.

Figure 12: An example of a Touch Input Device (TID) with various buttons. Source: "KDC Merge - concept refinement" NLR Contract Report NLR-CR-2016-653.

3.7 State of the art for explainable systems (ENAC)

Another needed enabler for the achievement of good Human AI teaming, is to ensure that the AI based systems are understood by operators, ensuring a shared system model and the possibility to anticipate system behaviour. Explainable AI (XAI) is an important aspect of artificial intelligence that focuses on making AI systems more transparent and understandable to humans. There are several rationales for the development and adoption of XAI:

- **Trust and Accountability:** XAI helps build trust in AI systems. When people can understand how AI makes decisions, they are more likely to trust and accept those decisions. It also provides a mechanism for holding AI systems accountable for their actions.
- **Bias and Fairness**: XAI can help identify and mitigate bias in AI systems. By providing transparency into the decision-making process, it becomes easier to detect and rectify instances where AI systems exhibit discriminatory behaviour.
- **User Understanding**: End-users and domain experts often need to understand how AI systems arrive at their conclusions. In fields like medicine or law, AI recommendations may need to be justified and comprehensible to professionals who rely on them.
- **Human-AI Collaboration:** In many scenarios, AI systems work alongside humans. Explainable AI can facilitate collaboration by providing insights into AI's reasoning, making it easier for humans to make informed decisions in partnership with AI.
- **AI model understanding:** The "black box" nature of AI can lead to fear and mistrust among the public. XAI can help alleviate these concerns by making AI systems more transparent and less mysterious.

In summary, XAI addresses a wide range of concerns related to trust, ethics, fairness, accountability, and practical utility in AI systems. It plays a crucial role in ensuring that AI technologies are deployed responsibly and effectively in the aviation domain. To further investigate the past, current, and future research perspectives of Explainable AI (XAI), the previous SESAR H2020 ARTIMATION project published one state-of-the-art review in the general XAI domain (Islam et al., 2022) and another in the specific aeronautical domain (Degas et al., 2022). As a lesson learned, numerous techniques and algorithms currently exist and are still under development to enhance the collaboration between humans and machines. In the future, as AI is integrated into the complex Air Traffic Management System, it should offer algorithm transparency and explanations to all stakeholders, including Air Traffic Control (ATC), providing three key pillars:

1. **Descriptive XAI:** The system should explain why specific actions are recommended, such as altering a flight plan to avoid a potential collision or addressing airspace congestion during take-off or landing. This information helps optimize system efficiency and safety.

2. **Predictive XAI:** The AI should project the consequences of various actions, allowing stakeholders to understand the outcomes of their decisions. For instance, if ATC takes certain actions to prevent a collision, it may lead to airport congestion. This helps stakeholders make informed choices based on "what if" scenarios.

3. **Prescriptive XAI**: In addition to descriptions and predictions, the AI should suggest appropriate actions with explanations. These recommendations consider safety as a priority but also account for factors like congestion, weather, ATC workload, pilot considerations, cost benefits, and environmental impacts. For example, if a "what if" analysis indicates high landing delays for Aircraft A, the prescriptive XAI would offer an immediate solution, like changing the flight path instead of altering altitude, to resolve the conflict.

These three levels of explainability have been identified, including description, prediction, and prescription. If the machine can effectively provide information at these three levels, it will help achieve the XAI goals mentioned earlier. However, while this is a theoretical statement, a significant amount of work remains to be done.

3.8 Conclusions

This chapter introduced the basic concepts that will be explored by the CODA project and that represent the fundamental bricks that will be used to build the CODA solution.

We started defining the main aim of the solution, which is to improve the teaming between humans (ATCos) and AI based systems. We also started presenting the main elements to be considered when trying to make this teaming more effective. In Chapter 5, we are going to better detail which of those aspects will be taken into consideration by the CODA solution and which are the expectation in terms of improvements of ATCos-Digital assistants' collaboration.

We then moved defining some enablers for the design of the CODA solution:

- The possibility to assess the mental states of ATCos
- The possibility to anticipate how those mental states will change in the future

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- The need for a strategy to manage the adaptation of AI to the current situation (considering the current traffic and the current and predicted mental states)
- The possibility for the AI to make the ATCos aware of what the system is doing and why

4 Generic use cases (ENAC)

The CODA project will focus on improving Human AI teaming for en-route ATCos. Nevertheless, the approach applied within the project could easily be adapted to different domains (especially safety critical socio-technical systems) and different contexts within the aviation domain.

This section provides a list of possible use cases of application of the proposed CODA solution in the aviation domain in general. In this part of the document, high level use cases will be presented to illustrate a set of activities that could be supported by the CODA system, without considering any project constraints and focus. In Section 5.3.3, a detailed description of the use case that will be investigated in the project will be provided.

These scenarios are a culmination of our comprehensive knowledge in the aeronautical domain, shaped through extensive discussions and brainstorming sessions. Our collaborative efforts involved a diverse group of individuals, including six (three ATCos' students and three ENACs' engineers) students passionate about air traffic control and aeronautical engineering, four (Workshop 1) and six (Workshop 2) air traffic controllers (ATCos) with expert-level experience, and one engineer with specialized knowledge in the field. Additionally, our research team, comprising one postdoctoral fellow and one dedicated researcher, played a crucial role in refining these scenarios. The development process was further enriched by conducting two interactive workshops, which provided a platform for in-depth analysis and creative exchange among participants from various backgrounds. This collective approach, leveraging the insights and expertise of both academic and professional perspectives, has been instrumental in creating realistic and forward-thinking scenarios for the aeronautical domain.

To elaborate on these scenarios, we employed an iterative process. We first assessed the capabilities of digital assistants and how we believe they can be beneficial for the air traffic control domain. Then we defined our efficiency criteria, which are based on mandatory criteria as well as so-called "good to have" ones. The mandatory criterion is safety, which must always be upheld. Next are more recent and, these days, almost obligatory factors, such as environmental constraints including fuel consumption, noise pollution, and environmental impact. Finally, there are the usual criteria, including traffic fluidity and optimization. Additionally, we have identified additional criteria to improve situational awareness, reduce cognitive workload, decrease user fatigue, and manage environmental complexity. While this list is not exhaustive, it represents the key criteria our scenarios must consider.

In order to generate valuable and interesting scenarios for a broader exploration of the design space, we decided to employ specific brainstorming strategies. Rather than solely seeking scenarios where automation can enhance air traffic controller activities, we chose to explore how automation and digital assistants could provide scenarios that challenge our established criteria. This approach, while not the most efficient way to produce realistic usage scenarios, remains interesting for a deeper investigation of our design space. This type of exploration is directly inspired by the seminal work of César A. Hidalgo in "How Humans Judge Machines" (https://www.judgingmachines.com/).

Figure 13: Photos taken during the workshop with ATCos in ENAC

In the upcoming sections, a few detailed scenarios will be presented, each shedding light on the multifaceted interactions between humans and the CODA AI system within the context of ATM. The first two scenarios present general use cases, providing a comprehensive view of the CODA AI's adaptive capabilities and decision-making prowess in the face of adverse weather conditions. These narratives underscore the importance of collaborative Human-AI teaming, showcasing how the AI seamlessly integrates with human operators to optimize air traffic routes and mitigate potential risks.

4.1 Scenario 1: Storm Deflection Symphony: Advancing Human-AI Collaboration for Dynamic Air Traffic Management

In the "Storm Deflection Symphony" scenario, the dynamic interplay between human and artificial intelligence (AI) in managing air traffic during a severe thunderstorm is explored. This scenario demonstrates how cutting-edge AI, utilizing extensive meteorological data, enhances situational awareness and supports Air Traffic Controllers (ATC) in decision-making. The AI system's capabilities extend to predictive modelling, risk assessment tailored to different aircraft, and the generation of multiple optimized route options. Crucially, this scenario underscores the concept of keeping humans “in the loop,” ensuring that ATCs maintain control and situational awareness. The AI’s explainable interface and natural language processing foster effective human-AI collaboration. Additionally, the scenario highlights potential pitfalls of AI, such as reliance on algorithms and ambiguity in complex situations. The iterative learning process from pilot feedback and the monitoring of AI's decision-

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making effectiveness illustrate the continuous evolution of AI systems in aviation, striving towards improved safety and efficiency.

Step 1: Initial Situation: Storm on an Air Route

The adaptable AI system, a cornerstone of the collaborative decision-making for ATC, employs cutting-edge algorithms to analyse an extensive array of meteorological data. This includes satellite imagery, weather radar scans, and ground station reports. By harnessing this wealth of information, the AI system not only identifies the presence of an intense thunderstorm but also conducts predictive modelling to anticipate its future path and intensity, enhancing the precision of its warnings.

To further enhance situational awareness, the AI system integrates historical data, considering past storm trajectories and their impact on air traffic. This comprehensive analysis enables the AI to provide a nuanced understanding of the evolving weather patterns, allowing for more informed decision-making by the Air Traffic Controller (ATC).

Step 2: AI Alert and Solution Research

The advanced AI system's alert mechanism is designed with multi-layered sophistication. In addition to notifying the ATC of the imminent danger, the system categorizes the level of severity, providing a nuanced assessment of the potential impact on different aircraft types. This granularity ensures that the ATC receives a detailed risk profile, allowing for more precise decision-making.

The AI system goes beyond suggesting alternative routes; it simulates various trajectory adjustments based on the unique operational characteristics of each aircraft in the affected airspace. By factoring in parameters such as fuel efficiency, aircraft weight, and passenger comfort, the AI presents the ATC with not just one but a range of optimized route options, providing flexibility and adaptability in decision-making.

Step 3: Notification of Situation and Solutions to the Controller

The real-time notification to the ATC is augmented with augmented reality overlays on the control screen. This immersive display presents a dynamic visualization of the storm's progression, supported by live feeds from relevant sensors. The AI system, recognizing the importance of human intuition, incorporates an explainable AI interface, providing the ATC with detailed insights into the decision-making process of the algorithm.

To further fortify human-AI collaboration, the notification system is equipped with natural language processing capabilities. It translates complex meteorological data into accessible insights, enabling effective communication between the AI and the human operator. This linguistic bridge ensures that the ATC comprehensively understands the risk factors and alternative routes, fostering a seamless collaboration in the decision-making process. This process ensures that the human operator remain “in the loop” and maintains situational awareness. This step exemplifies the synergy between human expertise and AI-driven recommendations in optimizing decision-making.

Step 4: Communication with the Pilots

In the communication phase, the ATC utilizes a comprehensive decision support interface that integrates real-time feedback from the pilots. This two-way communication channel allows for a dynamic exchange of information, enabling the pilots to share their observations and experiences in navigating the alternative routes suggested by the AI.

Moreover, the communication platform includes a machine learning component that continuously adapts to the evolving situation. It learns from pilot feedback and refines its future recommendations, creating a closed-loop system that improves its predictive accuracy over time. This iterative learning process ensures that the AI system becomes increasingly attuned to the nuances of real-world flight operations, enhancing its effectiveness in providing tailored recommendations.

Step 5: Monitoring and Adjustments

The AI system's monitoring capabilities extend beyond the immediate storm event. It utilizes machine learning algorithms to analyse the effectiveness of the implemented route adjustments. By tracking each aircraft's trajectory in real-time and comparing it to the initially recommended routes, the AI system generates performance metrics that contribute to ongoing improvements in its decision-making processes.

Furthermore, the monitoring phase includes a predictive element that anticipates the potential for route congestion or other operational challenges. This foresight enables the ATC to proactively address emerging issues, demonstrating a holistic approach to air traffic management that transcends immediate crisis response.

Step 6: Final Outcomes

The synergistic collaboration between human controllers and AI-driven systems results in a successful rerouting of flights around hazardous storm areas. This not only minimizes risks for passengers and crew but also mitigates delays to the greatest extent possible. The integration of AI has effectively reduced operator workload, enhanced overall performance, and demonstrated the project's goal of predicting and preventing potential problems in real-time.

These collaborative efforts between human controllers and the AI-driven system culminate in a comprehensive analysis of the outcomes. Post-event, the AI system generates a detailed report highlighting the efficacy of the implemented strategies. This report includes insights into the deviation from the initially predicted storm path, the adherence of pilots to the recommended alternative routes, and the overall impact on flight schedules. The outcome analysis becomes a valuable dataset for ongoing system refinement and training.

4.2 Scenario 2: Navigating Turbulence - Enhancing Adaptive Automation for Seamless Human-AI Collaboration in Adverse Weather Conditions

In the "Navigating Turbulence" scenario, the integration and challenges of adaptive automation in air traffic management (ATM) amidst adverse weather conditions are explored. This case highlights the collaboration between human air traffic controllers and an AI system in a high-traffic airspace, emphasizing the importance of enhanced situational awareness. A critical moment occurs when a technical glitch disrupts the smooth transition of control from AI to human, momentarily leaving the controller "out of the loop" and leading to information oversaturation. This incident underlines the potential pitfalls of AI, including the risk of over-reliance on automation and the necessity of maintaining human oversight. The AI's subsequent adaptive automation correction and use of explainable AI techniques underscore the need for clear human-AI communication and collaboration. The scenario concludes by emphasizing the importance of refining these processes to ensure safe and efficient ATM, particularly in complex operational scenarios where ambiguity and dynamic decision-making are prevalent.

Step 1: Initial Situation: Adverse Weather Conditions

In a bustling high-traffic airspace, the CODA's adaptable AI system is proactively managing air traffic during adverse weather conditions. The AI, driven by adaptive automation principles, dynamically allocates tasks in collaboration with human controllers to optimize efficiency, capacity, and safety in the Air Traffic Management (ATM) system. Understanding the significance of enhanced situational awareness, the AI incorporates real-time data from various sources, including aircraft sensors, to create a comprehensive picture of the evolving weather conditions in the airspace.

Step 2: AI Alert and Adaptive Automation

The CODA's AI system, equipped with enhanced weather prediction models, detects a rapidly intensifying storm along a major airway. Applying adaptive automation principles, the system seamlessly takes control of routine monitoring tasks, employing machine learning algorithms to evaluate alternative routes based on detailed aircraft capabilities. The AI system not only factors in aircraft performance but also considers real-time flight data, such as fuel levels and passenger load, to propose optimized trajectories that prioritize both efficiency and safety.

Step 3: Notification of Situation and Authority Transition to the Controller

As the AI system initiates the transition of authority back to the human controller, it leverages advanced communication interfaces to provide a detailed situational awareness report. A visual representation of the storm's progression, combined with haptic feedback, ensures that the ATC is fully cognizant of the critical weather conditions. The notification system incorporates context-aware messaging, acknowledging the potential for information overload during transitions, and employs layered communication strategies to convey the urgency of the situation effectively.

The ATC receives a notification from the AI presenting the critical weather conditions and its recommended course of action. However, there is a complication in the adaptive automation process. As the AI attempts to transition authority back to the human controller, a technical glitch occurs, disrupting the seamless handover. The ATC is momentarily left unaware of the transition and experiences a moment of being “out of the loop”.

Step 4: Controller's Response and Surfocused Conflict Handling

During the authority transition glitch, the ATC, now temporarily out of the loop, is momentarily unaware of the critical weather updates. Simultaneously, the system presents an emerging conflict in a different part of the airspace that requires immediate attention. The ATC, now experiencing a form of oversaturation, becomes fixated on resolving the conflict, inadvertently neglecting the storm-related information.

In response to the authority transition glitch, the ATC, momentarily out of the loop, relies on enhanced visualization tools displaying a comprehensive overview of the airspace. The CODA system, recognizing the potential for information oversaturation, integrates AI-driven prioritization algorithms to help the

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ATC focus on critical issues. The AI also employs natural language processing to provide auditory alerts, ensuring the controller remains cognizant of the storm-related information amid the emerging conflict in another part of the airspace.

Step 5: Adaptive Automation Correction and Collaboration

Recognizing the ATC's momentary lapse in situational awareness through eye-tracking technology, the CODA AI system triggers an adaptive automation correction. To facilitate the controller's reintegration, the AI temporarily reassumes control over routine tasks, allowing the human operator to regain situational awareness and comprehend the unfolding situation. The AI system, leveraging explainable AI techniques, communicates the unresolved weather situation, offering detailed insights into its decision-making process, and collaborates with the ATC to develop a cohesive strategy for both the impending storm and the emerging airspace conflict.

Step 6: Monitoring and Resolution

Post-correction, the AI system continues to monitor the evolving weather conditions with heightened vigilance. It employs predictive analytics to anticipate potential cascading effects and communicates real-time updates to the ATC through an intelligently designed user interface. The controller, now fully back in the loop, collaborates seamlessly with the AI to make informed decisions, leveraging the enhanced situational awareness provided by the adaptive automation correction.

Step 7: Final Outcomes

Despite the momentary glitch, the collaborative efforts between the AI system and the human controller successfully averted a potential crisis. The incident underscored the importance of refining adaptive automation principles to ensure smooth transitions between AI and human control while considering the nuances of situational awareness. The resolution not only showcases the project's commitment to maximizing Human-AI teaming but also emphasizes the critical role of enhanced awareness in navigating challenges posed by adverse weather conditions. This outcome significantly contributes to the strategic objectives of the CODA project, further advancing the efficiency and safety of the ATM system in complex operational environments.

4.3 Scenario 3: Harmony in Complexity - Advanced Human-AI Collaboration in Dynamic Air Traffic Management with Enhanced Weather Integration

In "Harmony in Complexity," the scenario navigates the delicate balance of Human-AI collaboration in air traffic management, addressing issues like situational awareness and the risk of humans being 'out of the loop.' The AI system, "CR Assistant," enhances decision-making amid ambiguous, high-stress situations, yet underscores potential AI pitfalls, such as over-reliance and decision-making ambiguity. While the AI aids in managing complex weather patterns and airspace congestion, its integration highlights the need for continuous human oversight to mitigate trust issues and ensure a harmonious blend of human intuition and AI precision in rapidly evolving air traffic environments.

Initial Situation: First Radar Image

In the immersive radar environment, a window labelled "AI," known as the "CR Assistant," appears in the bottom left corner of the screen, offering two potential modes.

Unfolding:

Time 1: As the situation unfolds, the AI system attuned to subtle cues detects that the air traffic controller (ATC), positioned in a bustling control centre, consistently directs their gaze towards conflict-ridden airspace, inadvertently neglecting aircraft hovering near the sector boundaries. This observation is facilitated by an advanced eye-tracking system, adding an extra layer of sophistication to the scenario.

Time 2: The AI, equipped with real-time weather updates, identifies a rapidly changing weather pattern near the sector's entry point. It considers the adverse weather conditions, such as turbulence and reduced visibility, contributing to the complexity of the airspace.

Time 3: A thoughtful suggestion to activate mode 1 is presented to the controller, with the label "MODE 1" highlighted in a distinctive colour. This mode, operating as an AI collaborator, focuses on managing aircraft approaching the sector entry. These are flights not currently on frequency and devoid of conflicts with other aircraft. The intention is to pre-emptively handle these incoming flights, alleviating the controller from the initial frequency management tasks.

Time 4: The controller, now dealing with a complex mix of conflicting airspace and adverse weather conditions, clicks on the AI window to seamlessly activate mode 1.

Time 5: The AI, utilizing its weather analysis capabilities, ensures that aircraft under its purview are highlighted on the radar screen in a colour carefully chosen not to disrupt the controller's visualization. This feature aids the controller in easily identifying aircraft that the AI is autonomously managing.

Time 6: After successfully resolving conflicts and navigating through the adverse weather, the ATC can regain control of the aircraft by bringing them back on frequency. To streamline the transition, the controller clicks on the "MODE 1" window, removing the highlighted labels and seamlessly integrating the aircraft back into their direct oversight.

As part of the comprehensive AI interface, the system incorporates pilot profiles, providing the controller with information on the experience levels and aircraft capabilities of the pilots involved. This additional detail contributes to a more nuanced decision-making process.

4.4 Scenario 4: Dynamic Conflict Resolution and AI Delegation in Air Traffic Management

In Scenario 4, "Dynamic Conflict Resolution and AI Delegation in Air Traffic Management," the intricate balance of human-AI collaboration is explored against the backdrop of air traffic control. It highlights the AI's role in managing complex situations, like conflict resolution and traffic monitoring, while keeping the human controller informed and in control. The scenario delves into the potential of AI to alleviate workload, yet also touches on the risks of over-reliance, possible ambiguity in AI decisions, and the importance of maintaining situational awareness. This situation underscores the need for trust and clear delineation of roles to avoid pitfalls where humans might become overly dependent on AI, leading to being 'out of the loop' in critical decision-making processes.

Time 1:

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The controller is focused on the dashed-line-surrounded area in the centre of their sector, with the need to resolve the conflict at 110, the conflict at 120, and monitor the descent of traffic from 110 to 90 to the east (Figure below). The traffic at 110 to the north requests avoidance of thunderstorm cells on the left, which must be authorized. The two aircraft to the west are free from any traffic and can be handed off to their respective next sectors. However, the controller does not have the necessary availability to perform this action, and the AI takes charge.

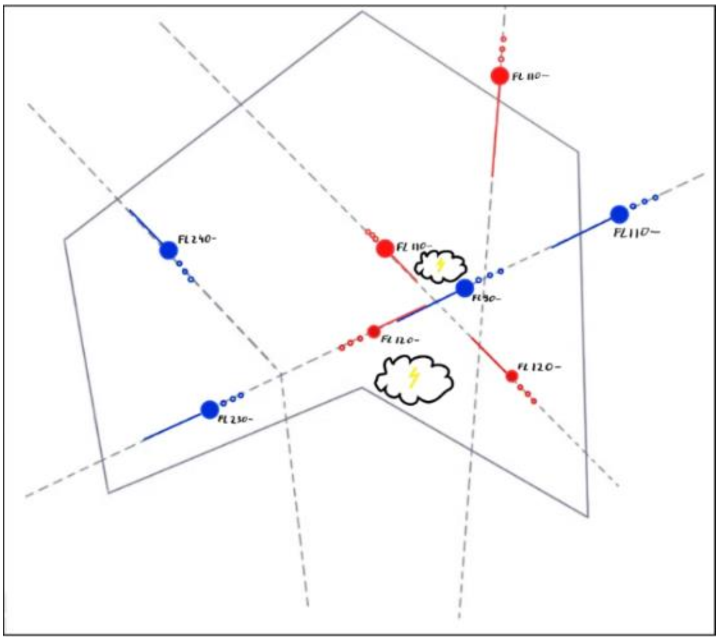

Figure 14: Urgency in a complex air traffic situation. The traffic at 110 to the north requests avoidance of thunderstorm cells on the left, which must be authorized.

Time 2:

The controller plans (or the AI proposes) to resolve the conflict at 110 by descending one of the two conflicting aircraft to level 100, which involves a temporary counter-parity to maintain separation minima. The conflict at 120 is laterally resolved by sequencing the aircraft coming from the southeast behind (the thunderstorm cell is located further south, as indicated). The aircraft from the east is stably cruising at level 90 (Figure below).

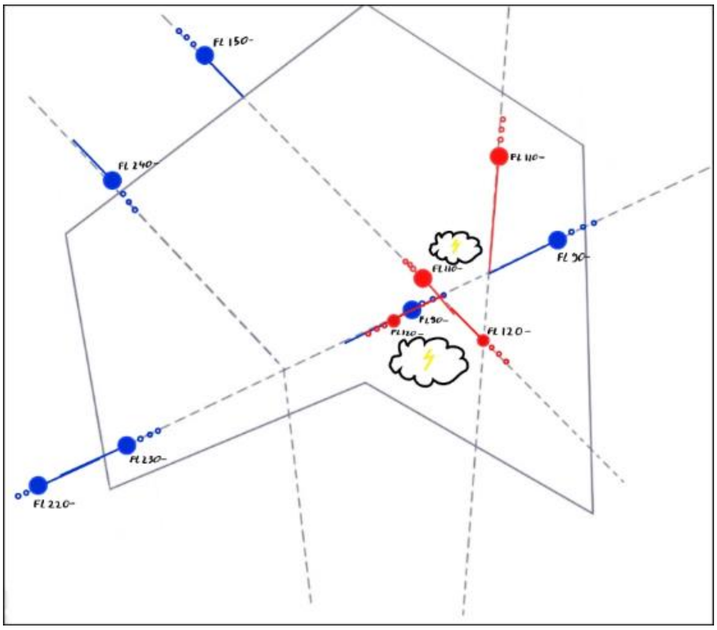

Figure 15: Urgency in a complex air traffic situation. The conflict at 120 is laterally resolved by sequencing the aircraft coming from the southeast behind.

<u>**Time 3:**</u>

Just after implementing its resolutions, the controller performs a radar sweep, realizing that six aircraft will soon establish contact with him, and he hasn't had the opportunity to integrate them. Understanding that these calls would be costly in time, frequency occupancy, and mental resources, which he currently lacks due to monitoring conflict evolution, the controller turns to the AI, accepting the system's proposal to manage the initial contact for these aircraft. Through the CPDLC system, each of these aircraft receives an initial message instructing them to follow their filed route and maintain their current altitude. A marker (here an asterisk) then appears on the reduced flight label, indicating to the controller that the AI has completed the previously described task (Figure below). Now, it is the controller's responsibility, once the conflicts are definitively resolved, to integrate and take control of these flights.

If one of these calling flights is an unknown Visual Flight Rules (VFR) to the system (outlined in the image), this resolution becomes complicated to implement. One solution could be to establish a separate frequency when the controller decides to delegate a portion of his work to the AI. Upon initial contact, an automatic message is sent to the pilot, indicating that they are not in contact with a controller and should remain in uncontrolled airspace.

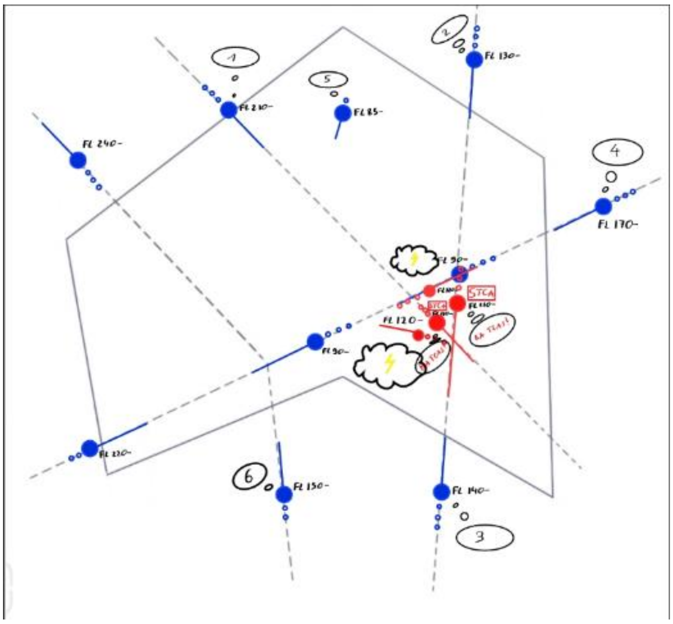

Figure 16: Urgency in a complex air traffic situation. Through the CPDLC system, each of these aircraft receives an initial message instructing them to follow their filed route and maintain their current altitude.

In this more operational scenario, the CODA AI system could significantly enhance task resolution by incorporating neurophysiological measures from the air traffic controller. By recording and analyzing real-time neurophysiological data, such as eye movement patterns, cognitive load, and stress levels, the AI system gains a nuanced understanding of the controller's mental state. This invaluable information can be utilized to precisely gauge the controller's focus, attention, and potential cognitive workload during critical moments of conflict resolution and decision-making. The AI system, through advanced algorithms, could dynamically adapt its level of assistance based on the controller's cognitive state, providing additional support during periods of increased workload or stress. This personalized and adaptive approach ensures optimal collaboration between the air traffic controller and the AI system, fostering a symbiotic relationship that maximizes efficiency and safety in air traffic management.

4.5 Scenario 5: AI Enhanced Air Traffic Control: Dynamic Adaptation in High-Stress Situations

In Scenario 5, "High-Level Scenario Based on Dynamic Task Allocation in High Traffic Situations," the focus is on managing the complexities of air traffic control during sudden traffic surges due to weather diversions. This scenario illustrates the integration of a digital assistant that uses biometric sensors to assess ATCos' mental states, addressing challenges like increased workload, communication overload, and conflict resolution in high-density airspace. It underscores the importance of maintaining human situational awareness and control, despite AI support, to mitigate the risks of over-reliance on technology and ensure safety. The scenario highlights potential AI pitfalls, including variability in response to unforeseen events and the need for transparent, adaptive decision-making to manage stress and cognitive load effectively.

Operational Context:

Amidst a surge in air traffic due to unexpected weather diversions, the operational context involves a complex scenario where the airspace experiences an influx of additional flights. The sudden increase in traffic necessitates swift and efficient decision-making by Air Traffic Control Officers (ATCos) to ensure the safety and orderly flow of aircraft.

Problematic Part:

In such a high-traffic situation, several challenges can emerge, posing potential risks to the safety of air traffic control operations:

- Increased Workload: The sudden influx of additional flights and the need for rerouting due to adverse weather conditions result in an increased workload for ATCos. They must simultaneously monitor multiple aircraft, assess the impact of weather on flight paths, and make quick decisions to ensure safe separation.
- Communication Overload: The spike in traffic may lead to a surge in communication exchanges between ATCos, pilots, and other stakeholders. This communication overload can result in delays, misunderstandings, and increased cognitive load on ATCos, potentially impacting their decision-making abilities.
- Conflict Resolution Challenges: With a higher density of aircraft in limited airspace, the likelihood of conflicts and potential safety hazards increases. ATCos face challenges in identifying and resolving conflicts promptly while managing the overall traffic flow.
- Variable Expertise Levels: The dynamic nature of the situation may lead to variations in the expertise levels of ATCos available to handle the increased workload. Some controllers may be more experienced in managing high-traffic scenarios, while others may find it challenging, leading to disparities in task execution.
- Fatigue and Stress: The intensified workload and the critical nature of decision-making during high-traffic situations can contribute to fatigue and increased stress levels among ATCos. Fatigued controllers may experience reduced situational awareness and slower response times, posing a risk to safety.

Addressing the Problems:

To address these challenges, the digital assistant dynamically assesses the mental states of ATCos, considering factors such as workload, stress levels, and expertise. It employs biometric sensors, including heart rate monitors and eye-tracking devices, to continuously monitor ATCos' conditions. The system then adapts task allocation, prioritizing routine tasks for ATCos experiencing elevated stress while redistributing more complex responsibilities to those with lower cognitive loads. This dynamic task allocation ensures a balanced workload, preventing burnout, and maintaining optimal situational awareness, ultimately enhancing the safety of air traffic control operations.

Monitoring Air Traffic Control Based on Physiological Measures:

The integration of a digital assistant equipped with advanced physiological monitoring capabilities provides a proactive approach to ensuring the well-being and performance of Air Traffic Control Officers (ATCos) during high-traffic situations. Leveraging the fluctuations in physiological measures, the digital assistant serves as a valuable tool in real-time monitoring and adaptation. Here's how the digital assistant can aid in this regard:

Continuous Biometric Monitoring:

- Heart Rate Monitoring: The digital assistant utilizes wearable heart rate monitors to continuously track the heart rates of ATCos. Elevations in heart rate can indicate increased stress levels and heightened cognitive load.
- Eye-Tracking Technology: By employing eye-tracking devices, the digital assistant monitors gaze patterns and blink rates. Prolonged staring or irregular blinking may signify fatigue or concentration issues, providing insights into ATCos' mental states.

Real-time Cognitive Load Assessment:

- EEG Devices for Brainwave Patterns: Wearable electroencephalogram (EEG) devices capture brainwave patterns, offering a direct insight into cognitive load variations. High-frequency brainwave patterns may indicate increased mental activity, while low-frequency patterns may suggest fatigue.
- Neurofeedback Systems: The digital assistant incorporates neurofeedback systems, providing real-time feedback to ATCos about their cognitive states. This instant awareness empowers controllers to self-regulate and manage workload more effectively.

Adaptive Task Allocation:

- Data Fusion and Decision Support: The digital assistant integrates physiological data with real-time operational data, creating a comprehensive picture of ATCos' mental and operational states. This data fusion enables the system to make informed decisions about task allocation.
- Machine Learning Algorithms: Employing machine learning algorithms, the digital assistant learns patterns of physiological responses during various operational scenarios. Over time, it becomes adept at predicting when ATCos may experience heightened stress or fatigue.

Dynamic Adaptation to Physiological Fluctuations:

- Prioritizing Tasks Based on Physiological State: When fluctuations in physiological measures are detected, the digital assistant dynamically adjusts task priorities. Routine tasks may be assigned to ATCos experiencing elevated stress, while more complex responsibilities may be redistributed to those with lower cognitive loads.
- Real-time Support and Alerts: In response to concerning physiological fluctuations, the digital assistant provides real-time support and alerts. It may suggest brief breaks, mindfulness exercises, or even redistributing tasks among the team to alleviate stress and maintain optimal performance.

Transparent Communication and Feedback:

- Explanation of Adaptive Decisions: The digital assistant transparently communicates the rationale behind adaptive decisions based on physiological measures. This not only fosters trust among ATCos but also ensures a clear understanding of why specific adjustments are made.
- Individualized Feedback and Support: Providing individualized feedback, the digital assistant offers insights into the impact of physiological fluctuations on performance. It may recommend personalized strategies for stress management or workload distribution, tailored to each ATCo.

By actively monitoring the physiological measures of ATCos and leveraging this information for dynamic adaptation, the digital assistant becomes a valuable ally in maintaining optimal air traffic control operations. This approach not only enhances safety by preventing potential cognitive fatigue but also contributes to the overall well-being and resilience of the ATCo team during challenging operational scenarios.

Collaborative Decision-Making in Unforeseen Events:

The digital assistant integrates sentiment analysis and workload prediction algorithms, complemented by electroencephalogram (EEG) devices, to assess and anticipate ATCos' mental states.

In response to an unplanned event, such as an aircraft experiencing a medical emergency, the digital assistant assesses ATCos' mental states. EEG devices measure brainwave patterns, providing insights into cognitive load. The system initiates a collaborative decision-making session, allocating tasks based on workload predictions, individual stress levels, and neurophysiological signals. This ensures that ATCos can collectively address the emergency while adapting to their varying mental states.

Real-time Conflict Resolution and Traffic Flow Optimization:

The digital assistant incorporates neurofeedback systems to measure ATCos' mental states during conflict resolution, enhancing real-time adaptability.

As the system identifies a potential conflict between two aircraft, it assesses ATCos' mental states using neurofeedback systems. The real-time feedback from neurophysiological signals, such as brainwave patterns, aids in understanding cognitive load. The digital assistant dynamically adjusts task allocation, providing additional support to the ATCo handling multiple conflicts. It transparently communicates this decision, explaining that the adaptation is based on workload considerations and the cognitive load of the ATCos involved.

Adaptive Response to Unplanned Air Traffic Events:

The digital assistant integrates wearable EEG devices and fatigue prediction algorithms to assess ATCos' mental states during unplanned events.

In the event of an unscheduled landing due to an aircraft experiencing technical issues, the digital assistant assesses ATCos' mental states. Wearable EEG devices provide insights into cognitive load and fatigue levels. The system dynamically adapts, reallocating tasks to minimize the impact on stressed ATCos. Additionally, it adjusts communication strategies, providing clear and concise information to maintain situational awareness. The digital assistant transparently communicates the adaptive strategy, ensuring all ATCos are aware of the adjustments made.

Enhanced Communication and Information Sharing:

The digital assistant employs natural language processing and fatigue prediction algorithms, supplemented by eye-tracking technology, to assess ATCos' mental states during communication-intensive scenarios.

During a prolonged communication session involving coordination with multiple sectors, the digital assistant assesses ATCos' mental states. Eye-tracking technology monitors attention levels, while fatigue prediction algorithms anticipate potential cognitive fatigue. The system dynamically adjusts the pace of information sharing and communication intervals, optimizing the timing of critical updates. It transparently informs the team about the adaptive communication strategy, ensuring that information is conveyed effectively while considering the cognitive load of the ATCos involved.

By incorporating tools to measure neurophysiological signals, such as EEG devices, heart rate monitors, and eye-tracking technology, the scenarios are enhanced with a deeper understanding of ATCos' mental states. These tools provide valuable insights for the digital assistant to adapt dynamically, ensuring a supportive and efficient operational environment.

Together, these different scenarios offer a comprehensive exploration of the CODA AI system, showcasing its adaptability, decision-making precision, and collaborative potential in optimizing both the strategic and operational facets of ATM systems. Through these narratives, the aim is to provide a nuanced understanding of how Human-AI teaming contributes to enhanced performance, risk mitigation, and the overarching objectives of the CODA project.

4.6 User-Case conclusions

The diverse range of scenarios outlined in the user-case section of the CODA project underscores the multifaceted potential of AI and digital assistant technologies in transforming ATM. These scenarios, though illustrative, offer a glimpse into the breadth of applications and the depth of impact that such technologies can have in the aviation domain.

In the user-case scenarios for the CODA project, key points emerge that collectively illustrate the transformative potential of AI and digital assistants in ATM. These scenarios underscore enhanced situational awareness, where CODA's advanced capabilities provide ATCos with critical insights in complex airspace, ensuring better decision-making and safety. Emphasizing environmental efficiency, the scenarios explore route optimization for reduced fuel consumption and noise pollution, aligning with today’s environmental concerns. A significant focus is placed on cognitive workload management, highlighting how AI can alleviate the burden on ATCos, leading to increased efficiency and reduced fatigue. Lastly, the scenarios address airspace capacity enhancement and noise abatement strategies, demonstrating CODA's role in improving airspace utilization while being mindful of community impact. These key points collectively highlight the breadth of CODA’s application in revolutionizing ATM, balancing technological advancement with human-centric considerations.

These scenarios closely align with the core objectives of the CODA project, particularly in highlighting the critical roles of AI and digital assistants. CODA's emphasis is on ensuring a seamless alignment between the contextually captured states and the prevailing aeronautical situations. This alignment aims to bridge the gap between the digital capabilities of AI and the real-world dynamics of ATM, all while keeping the human user at the centre of the decision-making process.

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5 Operational service and environment definition (OSED)

This chapter describes the SESAR solution under the scope of the document, detailing the operational environment and operational concept aspects.

5.1 SESAR Solution 0447 - Adaptive System based on Controller Status for Enhanced Human-AI Teaming: a summary

The CODA solution falls under the **ATM OPERATIONAL SOLUTION** category, as it provides an operational improvement (OI) with a supporting Enabler (i.e. the CODA system) able to support current and future ATM solutions.

The objective of the CODA solution is **to increase the efficiency, capacity, and safety of ATM maximising Human-AI teaming.**

To do so, the project will develop a system (up to TRL2) in which **tasks are performed collaboratively by hybrid human-machine teams and dynamically allocated through adaptive automation principles.**

The system **predicts** relevant mental states of en-route air traffic controllers so to anticipate possible problems and **trigger specific actions** (such as the activation of Digital Assistants), as briefly summarised in the following image:

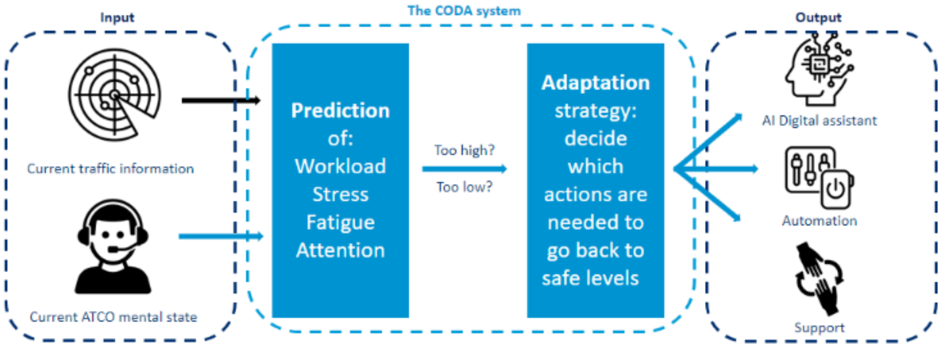

Figure 17: Brief summary of the CODA concept (blue elements are the ones addressed by the project)

Specifically, the system is based on several components:

- **Current mental state assessment:** assess the current status of the operator (e.g. level of workload, stress and other relevant human factors) [OBJ3][3].
- **Tasks prediction:** A first one will use current traffic data to foresee the future tasks that the operator will need to perform in the future [OBJ1][4].

- [3] The details of how this module works and how it will interact with the prediction one will be provided in D4.1 Indexes description and integration with the prediction models.
- [4] The details of how this module works will be provided in D3.1 ATCO Tasks prediction model.

- **Mental states prediction:** calculate the impact of predicted tasks in terms of cognitive complexity [OBJ2].
- **System adaptation:** With the information gathered by the previous models, the system will predict the future mental state of the operator and will act accordingly [OBJ4][5].

The following image provides a simplified overview of the CODA solution.

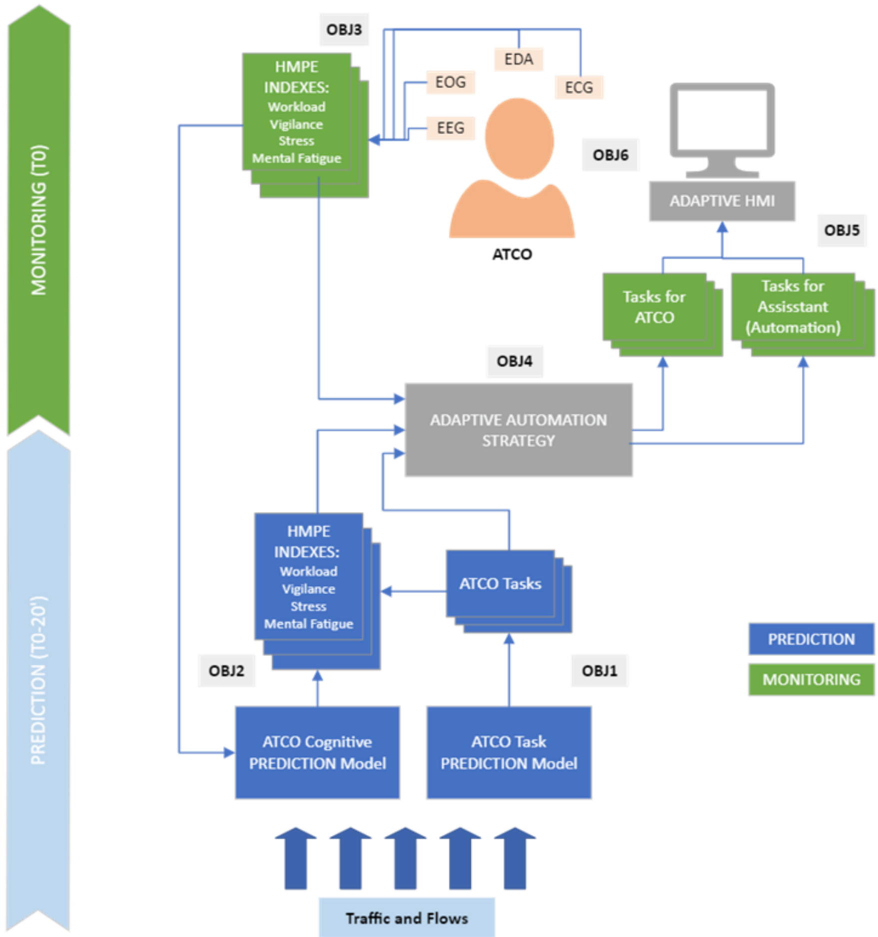

Figure 18: SESAR Solution 0447 - Adaptive System based on Controller Status for Enhanced Human-AI Teaming: concept

To provide an example of how the system could work, let's imagine that an ATCo is managing a complex traffic situation, experiencing a medium level of workload. The system is aware of this (thanks to the neurophysiological assessment) and predicts that the additional upcoming tasks the ATCo will need to take care of will increase their workload, exceeding the maximum an operator can handle. To avoid this future problem, the system decides how to act, following an adaptation strategy: it may decide to increment the level of automation, enabling additional AI based tools, or to request a sector splitting, or even contact network management to ask for some regulations to be issued.

- [5] The details of how this module works will be provided in D5.1 Adaptation and Human AI interaction strategy and teaming playbook

Regarding the wider expected impact of the project, CODA results are expected to make a difference in terms of impact, beyond the immediate scope and duration of the project. In particular, the CODA project will produce the preliminary conceptual design of the ATCo Digital Assistance Tool, providing understanding of how the tool's basic principles will be used (Please refer to section 1.2 Methodology)

In the long term, the CODA project will have an impact in many of the research and innovation needs addressed in the **SRIA to achieve the Digital European Sky programme**. In detail, the CODA project will have an impact on:

- *the Connected and Automated ATM.* The Digital Assistance Tool will boost the level of automation in the ATM. This will contribute to achieving the European ATM Master Plan vision to reach at least level 2 (task execution support) for all ATC tasks and up to level 4 (high automation) for some of the tasks.
- *Capacity-on-demand and dynamic airspace.* The CODA system will allow a dynamic reconfiguration of resources (HUMAN-AI TEAMING) and new capacity-on-demand (ADAPTIVE AUTOMATION FOR TASK ALLOCATION AND EXECUTION) services to maintain safe, resilient, smooth and efficient air transport operations while allowing for the optimisation of trajectories, even at busy periods.
- *Artificial intelligence (AI) for aviation.* The predictivity and prescriptibility of the system will optimise the ability to identify potentially problematic solutions and to correct them before the event occurs.

The CODA Project demonstrates a significant contribution to the realisation of the **Digital European Sky vision** (SESAR Phase D) in relation to achieving:

- *fully scalable services supported by a digital eco-system*, providing an enabler for adaptable systems able to effectively respond and anticipate disruptions and problematic situations
- *high and full automation* (level 4/5), providing a concrete example of a system adapting the level of automation to the contextual condition and the states of operators, ensuring the best possible level of automation in the different conditions

SESAR solution ID	SESAR solution title	SESAR solution definition	Justification
SESAR Solution 0447	Adaptive System based on Controller Status to enhance Human-AI Teaming	The Solution enables a better integration of any AI-based tools supporting the work of En-Route Air Traffic Controllers (but could easily be applied to other controllers' roles), improving teaming, wellbeing, safety and performance, and keeping the mental state of the controller within safe boundaries. More specifically, it enhances adaptability in highly automated systems by managing the interaction of AI tools and other support systems with Air Traffic Controllers based on their current and anticipated mental states. The system includes: ● A tasks prediction module ● A mental states assessment module ● A mental states prediction module ● An adaptive automation strategy module	The expected benefits for the main targeted stakeholder (ANSPs) will be to: ● Improve operations predictability ● Improve/Maintain level of safety in ATM ● Increase airspace capacity ● Increase operational efficiency ● Reduce costs due to inefficiency and unexpected complex/unsafe situations.

Table 3: SESAR Solution 0447 - Adaptive System based on Controller Status for Enhanced Human-AI Teaming: scope

5.1.1 Deviations with respect to the SESAR solution definition

No deviation with respect to the SESAR solution definition were identified.

5.2 Detailed operational environment

5.2.1 Operational characteristics

Although the CODA system is potentially applicable to different operational context, in the frame of the ongoing research activities the focus will be on the current **en-route commercial air traffic (CAT) in the European airspace**. That is with a focus on:

- Class A airspace where the ATCo provides 5NM or 1000ft separation
- Commercial air traffic (CAT) operating under IFR

- Higher altitudes: between FL245 – FL410

It is expected that the adaptive ATC system will be integrated in future complex environment in which the controllers' activity is supported by **high level of automation**.

5.2.2 Roles and responsibilities

The operational environment is focussed on air traffic control services for en route traffic. Air traffic control services are provided by one or more *executive controllers* supported by *planners* (assistant controller) within a given sector within an airspace.
Air traffic control services has several interfaces that should be considered too, notably air traffic flow management and airspace management, as illustrated in Figure below.

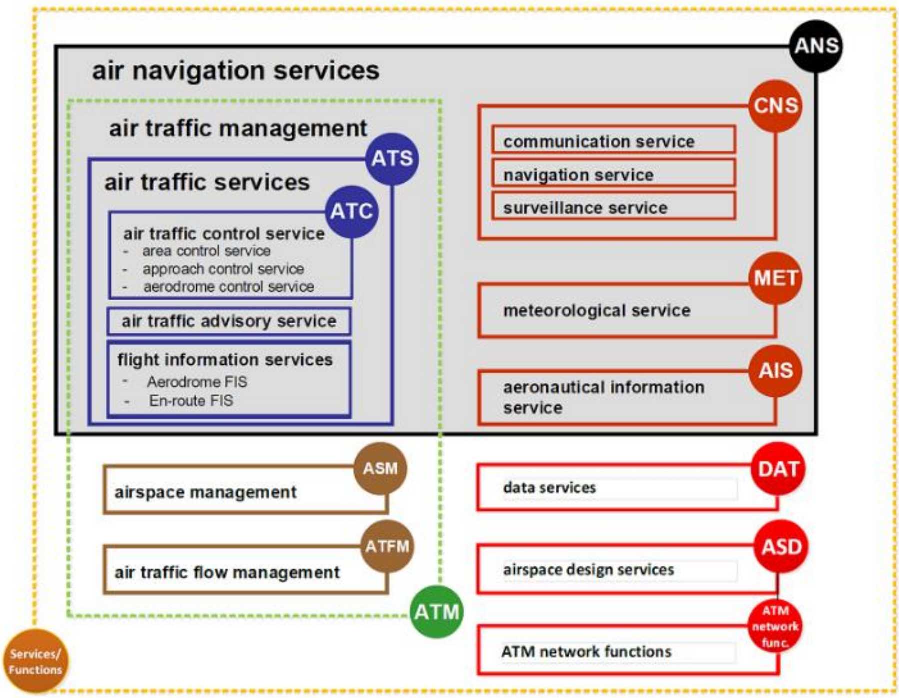

Figure 19: Operational environment

Air Traffic Flow Management (ATFM) aims to ensure optimal traffic flow when demand is expected to exceed the available capacity of the ATC system. It comprises activities related to traffic organization and handling in a way that is safe, orderly, expeditious and kept within the capacity. ATC capacity reflects the ability of the system to provide service and is expressed in numbers of aircraft entering a specified portion of the airspace in a given period of time. Depending on the traffic demand, restrictions can be given or the sectorisation can be adjusted. ATFM is performed by the Flow Manager Position (FMP) in coordination with the Supervisor.
En route, air traffic control is provided in the airspace of a given flight information region (FIR). Depending on the traffic load, the airspace is split into several sectors which can be merged again when the traffic load permits. This process is called sectorisation and is performed by the supervisor. Increased capacity demand is generally met by provision of more sectors. Usually, the demand is

calculated as short-term operational predictions based on planned flights. Opening/closing of sectors should closely monitor the demand to achieve efficient use of all available resources.
Within this operational environment, the functions of supervisor, flow manager position, executive controller and planners are included in the scope.
European functions managing the pan-European airspace, such as the Network Manager, are out of scope.
The CODA solution will be tested in the project as an additional support for the executive controller, without changing their roles.

5.2.3 CNS/ATS description

The air traffic controller is supported by an air traffic control system (ATCS) via an operational display, i.e. the Human-Machine Interface (HMI). The ATCS consists of several subsystems for (radar-based) surveillance, (R/T-based) communication and (flight) data processing.

In this section only surveillance and communication are described in more detail. The current available systems for navigation will be available and will not be affected because of the CODA project.

Surveillance

Primary and secondary radars are used to enhance a controller's situational awareness within the assigned airspace via an operational display. All types of aircraft send back primary echoes to controllers' screens and transponder-equipped aircraft reply to secondary radar interrogations by providing an ID (Mode A), an altitude (Mode C) and/or a unique callsign (Mode S). Mode S provides a data downlink of flight parameters via secondary surveillance radars allowing radar processing systems and therefore controllers to see various data on a flight, including airframe unique id, indicated airspeed and flight director selected level, amongst others.

Based on these inputs with added data from other radar sources, the air traffic situation is displayed. By correlating the radar information with the electronic flight plans additional information is available on the operational display.

For en route traffic, air traffic control services are provided from Area Control Centers (ACCs). Currently, the level of automation varies per ACC. Ranging from basic systems, consisting of a communication system only, to advanced systems where the functionality is complemented by various tools. Examples of these tools are:

- STCA (Short Term Conflict Alert: a tool that checks possible conflicting trajectories and alerts the controller. The STCA is activated about 2 minutes (or even less in approach context) prior to the loss of separation. The algorithms used may also provide in some systems a possible vectoring solution, that is, the way to turn or descend/climb the aircraft to avoid infringing the minimum safety distance or altitude clearance.
- Medium Term Conflict Detection (MTCD) providing conflict advisories up to 30 minutes in advance complemented by a suite of assistance tools that assist in evaluating resolution options and pilot requests. Today several MTCD tools are available in Europe, such as iFACTS (NATS), ERATO (DSNA), VAFORIT (DFS). The SESAR Programme is planning to launch new MTCD concepts.

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All these tools are aimed at providing alerts (and in some cases proposes a resolution) to the controller based on the current situation and a predicted future situation.

Communication

Generally, communication is performed via R/T. A different type of communication is the CPDLC. The Controller and Pilot Data Link Communication (CPDLC) is a digital data link between the air traffic control system and the aircraft. Using this link CPDLC allows digital messages to be sent between controllers and pilots, avoiding the need to use radiotelephony, reducing the controllers' workload as a large fraction of all air-to-ground communications involves the hand-off of a flight from one sector to another, allowing controllers to focus on more complex and challenging tasks.

5.2.4 Applicable standards and regulations

In principle all standards and regulations that apply within the European airspace are applicable. The regulation governing ATM/ANS is particularly relevant, i.e. Commission Implementing Regulation (EU) 2017/373 of 1 March 2017 laying down common requirements for providers of air traffic management/air navigation services and other air traffic management network functions and their oversight.

Additionally, there are requirements involving

- Ground Equipment: Commission Delegated Regulation (EU) 2023/1768 of 14 July 2023 and Commission Implementing Regulation (EU) 2023/1769 of 12 September 2023
- Air Traffic Controllers: Commission Regulation (EU) 2015/340 of 20 February 2015 — Air Traffic Controllers' Licences and Certificates
- Airspace Usage:
    - Commission Regulation (EU) No 1332/2011 of 16 September 2011 — Airspace Usage Requirements and Operating Procedures for Airborne Collision Avoidance (ACAS II)
    - Commission Implementing Regulation (EU) 2018/1048 of 18 July 2018 — Airspace Usage Requirements and Operating Procedures concerning Performance-Based Navigation (PBN)
    - Commission Implementing Regulation (EU) 2023/1770 of 12 September 2023 — Provisions on aircraft equipment required for the use of the Single European Sky airspace and operating rules related to the use of the Single European Sky airspace (AUR.IR)
- Standardised European Rules of the Air: Commission Implementing Regulation (EU) No 923/2012 of 26 September 2012 — SERA

5.3 Detailed operating method

In principle, the functions within the operating environment are not changed in the new SESAR operating environment (due to the adaptive systems). Only **the systems providing the support** for the functions and roles are modified. They are providing support in an adaptive manner.

5.3.1 Detailed operating method

N/A

5.3.2 New SESAR operating method

N/A

5.3.3 CODA Use case

The project will detail the support to **en-route controllers** use case.

This specific use case consider an **executive ATCo**, working in a high traffic environment.

The EXE ATCo will be supported by the CODA system.

They will wear monitoring devices so to **assess the current level** of 4 mental states (workload, fatigue, stress, attention).

The system will predict the future mental states according to the incoming traffic and will act in case **one or more of the assessed mental states go out of a safe range**.

The system will act activating/de-activating specific high automation support or AI Digital assistants support, and/or communicating the status to other roles (e.g. Supervisor/Flow manager), still to be identified (see D6.1 ERP for the description of the automations and AI tools that will be simulated).

The project will detail this specific use case in several scenarios that will be used for the validation of the solution. Those scenarios will be focused on changing complexity levels (from medium to very high) able to trigger different mental states levels and do system adaptation to prevent unsafe situations (see D6.1 ERP).

5.3.4 Differences between new and previous operating methods

Activities (in the SESAR architecture) that are impacted by the SESAR solution	Current operating method	New operating method
Executive ATCo activities	Supporting tools are selected and use by ATCo	Supporting tools and external aid is automatically triggered when unsafe mental states situations are predicted.

Table 4: differences between the new and the previous operating method

5.3.5 Initial feedback on the CODA concept

The first Advisory Board workshop was conducted on December 15, 2023, with 22 participants, with the contribution of eight External Advisory board members representing regulators, ATCO representative associations, other research projects representative and domain related press representative. During this workshop, the basic characteristics of the CODA concept have been presented. We report here some of the feedback gathered (see D6.3 ERR for full details and the results of the workshop).

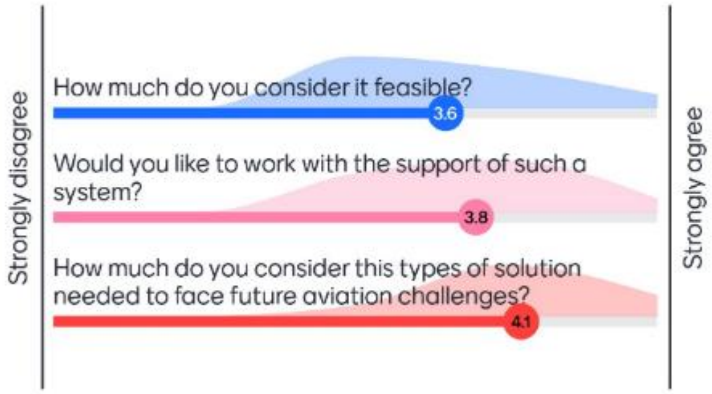

Figure 20: Initial high level feedback on the CODA concept on the scale of 1 to 5

In general, as demonstrated in Figure 20, the AB members agreed with the feasibility and expected benefits of the CODA system. Many of them expressed to be in favour of a system that provides adaptation depending on ATCos conditions. Furthermore, most of them consider it as needed to support future complex hybrid AI-Human scenarios.

6 Key assumptions

In the context of CODA, some assumptions have been made in terms of **enablers for an effective use of the proposed system in future operations**.

- **Operators (i.e. enroute controllers) can be monitored in real time:** the project proposes a set of tools that can be used for assessing in real time the mental states of controllers. The actual use of similar tools is impacted by several considerations that are not technical ones. The use of alternatives monitoring tools can influence the acceptability of such an assessment, as well as the data management process and privacy management of the acquired data.
- **AI based Digital assistants and high-level automation tools will be developed and implemented in the ATM domain:** CODA makes ATM systems adaptable to specific situations (e.g. high peak workload), also by acting on the behaviour of supporting tools. The more those tools are available, the more CODA will prove its effectiveness in preventing unwanted situations.

7 References

Applicable documents

This OSED complies with the requirements set out in the following documents:

Project and programme management

101114765 CODA Grant Agreement

SESAR 3 JU Project Handbook – Programme Execution Framework

Reference documents

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Appendix A

Stakeholder identification and benefit impact mechanisms (BIM)

A.1 Stakeholders' identification and expectations

The project identified a list of stakeholders impacted by the project, listed in the following table.

The next paragraph will present the BIM related to the ATM related ones.

Stakeholder	Involvement	Why it matters to the stakeholder
Scientific community (Universities, research institutions, EU projects, educational institutions)	To disseminate the project objectives, intermediate and results of the project, potentially finding synergies with other projects/approaches focused on the implementation of higher levels of automation and AI within ATM through scientific dissemination, workshops, etc.	To raise mutual awareness of approaches results potentially resulting in further collaborations To make students and academia aware of advanced AI solutions in ATM, helping to entice them to this knowledge area.
Institutional bodies (EU and EC, European Joint Undertakings, EASA, Policy makers, Regulatory and safety agencies, Standard making bodies, National bodies, Certification bodies).	To provide an actionable roadmap for the progressive and controlled deployment of AI solutions through direct links though the Advisory Board and dissemination events	To help facilitate the progressive and safe introduction of AI solutions in ATM in a controlled way, by implementing actual examples of potential uses to help confidence to be built on the users and regulators and helping define future safety/security/privacy constraints for its implementation.
Industry (ATM automation systems providers).	To make industry aware of the potential and results of our project for final implementation using direct links with industries and dissemination events	To provide a clear path for the higher TRLs implementation of the solution, and potentially opening the way to more AI based solutions implementation.
General public, media.	To raise awareness on CODA objectives and results in the general public	To make clear the value of the project and the benefits for

		citizens, especially in terms of safety and economy impacts.
Users (ATCos, ANSPs, NM).	To promote solution benefits and potential applications to the ANSPs and Network Management stakeholders at large using NM fora and communication channels, and direct relations with some ANSPs and ATCo organizations (e.g., ENAIRE, IFATCA).	To start the journey to finally deploy in future a CODA based solution, with the help of the industry to reach higher levels of TRL, in actual operations To inform Decision Makers and incentivise operational stakeholders to adopt CODA solution (see BIM for additional details)

Table 5: stakeholders' expectations and involvement

A.2 Benefits impact mechanisms (BIM)

Preamble: CODA is expected to enable systems adaptability to users' status. The following paragraphs will summarise related expected benefits. It must be noted that the magnitude of the impact is highly influenced by the effectiveness and efficiency of the different automations and AI assistants that will be triggered by the system. We focus here on the two main changes introduced by the CODA system:

- Adaptability of ATM En-route system for executive controller
    - Adaptability of task allocation between operator and machine (automation, AI)
    - Adaptability of the interface used by the operator

Two main impacted stakeholders have been identified:

- Air Navigation Services Providers (ANSPs)
- Airspace Users (AU)

Hereafter is a high-level description of the Benefit and Impact Mechanism (BIM) for each impacted Stakeholder. These benefit mechanisms might also be refined in the context of the different Validation Exercises related to the Solution.

Benefit and Impact Mechanism consists of the measurement of different KPIs that will be calculated during validation exercises by comparing base scenarios with new scenarios.

The BIM diagram has been organised in columns:

- Changes: Short description of a change brought about by the OI Step
- Performance Indicators / Metrics: Aspects which can be measured (or calculated from other metrics) to identify if the expected positive and negative impacts are realised. These need to be things that can be measured in the validation exercises.
- Impacts (Positive or Negative): Describes the expected positive or negative impacts
- KPA / TA Impacted: The KPA, which is related to the Impact, as defined in the SESAR2020 Performance Framework

The blue arrows show the relationship among the elements in the different columns

The red/green/white arrows show the expected impact, applying the following code:

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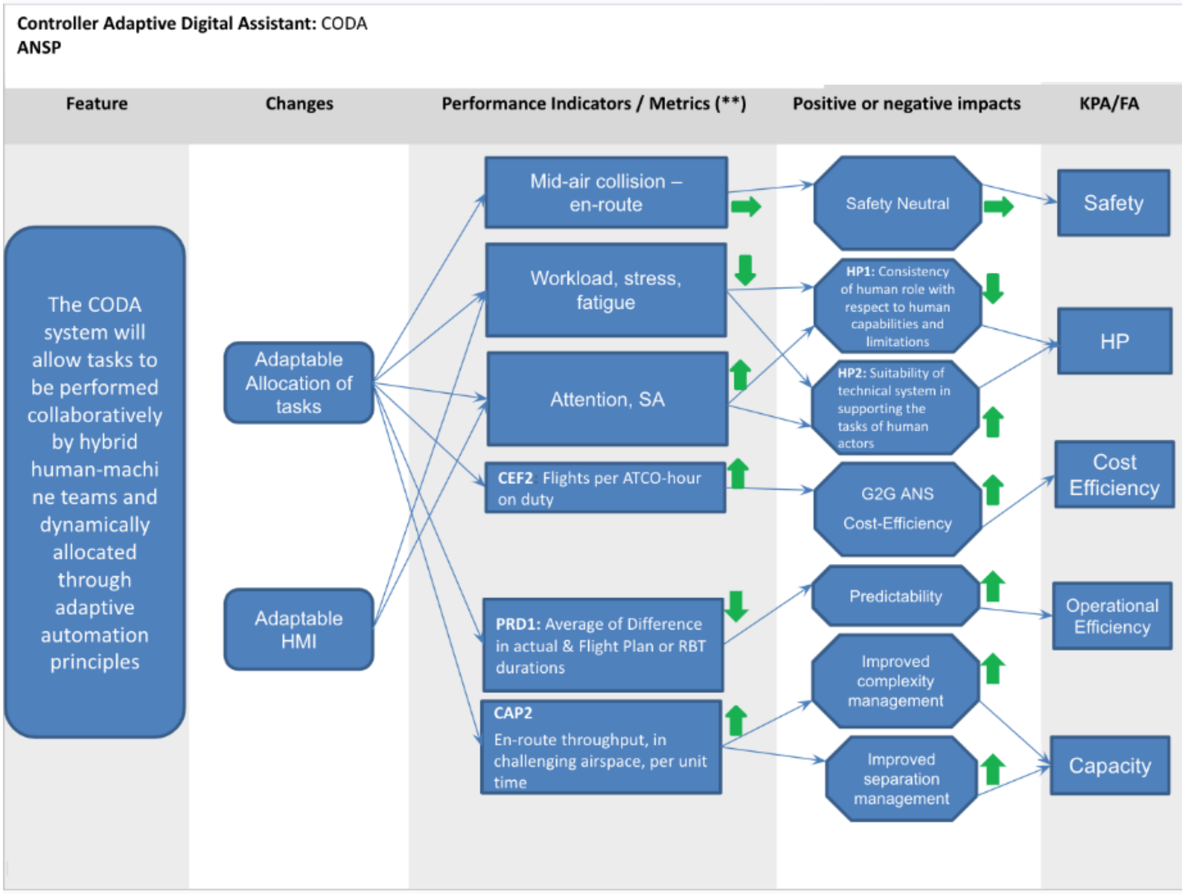
Arrow	Indication
↓	A beneficial decrease
↑	A detrimental increase
↑	A beneficial increase
↓	A detrimental decrease
⇨	A change in the indicator, a positive or negative impact is expected but with current knowledge the direction is still not clear.

The following tables describe per main stakeholder each change that is expected to take place because of the use of the solution, the variation for each KPI and the KPA (focus area) impacted.

A.1.1 Benefits impact mechanisms for ANSPs

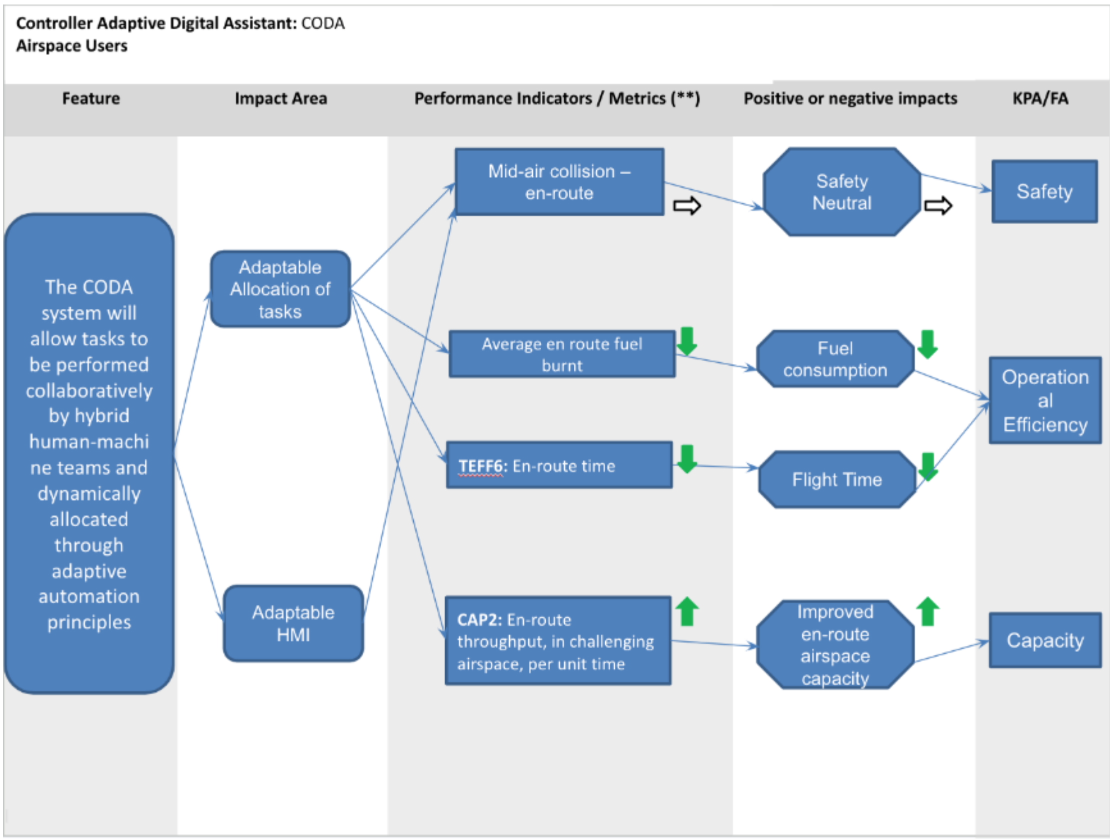


As mentioned above, the changes introduced by the CODA system:

- Adaptability of ATM En-route system for executive controller
  - Adaptability of task allocation between operator and machine (automation, AI)
  - Adaptability of the interface used by the operator

The changes introduced by the CODA system regarding ANSPs will have a positive impact in terms of cost efficiency, operational efficiency, and capacity. The reallocation of tasks between human-AI will allow for more efficient flight management, as during peak workloads, certain tasks can be performed by artificial intelligence, such as calculating optimal routes, thereby increasing capacity and reducing costs. Sharing this workload will also have positive impacts in terms of Human Performance. In fact, when AI calculates excessive workloads, it helps the Air Traffic Controller (ATCO) by reducing fatigue, workload, and stress. Thanks to the adaptable HMI (Human-Machine Interface), the system will also enhance the ATCO's attention and Situational Awareness (SA) by deciding, based on the workload, which information to display.

A.1.2 Benefits impact mechanisms for Airspace Users



The changes brought by the CODA system also will impact Airspace users. The improved ATCOs' performance will directly benefit also AU in terms of improved capacity and efficiency.

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