D1.1 State of the Art Review

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Authors of the document

Name/Beneficiary	Position/Title	
Javier Nuñez /SKLE		19/03/2018
Adrián Colomer/CVBLab		16/05/2019
Stefano Bonelli/ DBL		27/05/2019
Javier Nuñez /SKLE		31/05/2019
Jean-Paul Imbert		27/05/2019
Géraud Granger		27/05/2019

Reviewers internal to the project

Name/Beneficiary	Position/Title	Date
Geraud Granger		07/06/2019
Antonio L. Rodriguez		27/06/2019

Approved for submission to the JU By — Representatives of beneficiaries involved in the project

Name/Beneficiary	Position/Title	Date

Rejected By - Representatives of beneficiaries involved in the project

Name/Beneficiary	Position/Title	Date

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HARVIS

HUMAN AIRCRAFT ROADMAP FOR VIRTUAL INTELLIGENT SYSTEM

This deliverable has received funding from the Clean Sky 2 Joint Undertaking under grant agreement No 831884 under European Union's Horizon 2020 research and innovation.

Abstract

The main goal of the HARVIS Project is to identify how cognitive computing algorithms, implemented in a digital assistant, could support the decision-making of single pilots in complex situations. The first step to reach this objective is to define what is the state of the art of Artificial Intelligence, and in which context it is expected to work into, having 2035 as a target reference.

This document presents the results of the state-of-the-art analysis carried out on:

- **The future aviation scenario:** what we expect the roles, the technologies, the procedures and the traffic will look like in 2035+.
- **Single pilot operations:** what it is expected to change in the cockpit from the point of view of tasks allocations and available supporting technologies.
- **The Artificial Intelligence:** which are the capabilities of Machine Learning (ML) and Cognitive Computing (CC) algorithms and what AI based technologies are (and will be) able to do, not only in aviation but also in other domains.
- **Human Factors:** how the interaction between pilots and automation is expected to change, especially when dealing with highly automated systems.
- **Human-Machine Interface:** which interfaces could facilitate a safe and proficient interaction with those systems, reaching a perfect balance between humans and automation.

The document also describes the **architecture** behind the Virtual Pilot Assistant concept.

These are the basic information the project will use:

1. to develop the **concept** of an AI based virtual assistant able to enable and support Single Pilot Operations (that will be presented in D2.1 Analysis of Potential Cognitive Computing Aided Tasks) and
2. as a starting point in the definition of a **roadmap** highlighting the steps needed, in terms of technology development, interaction design and training, to develop such an assistant (that will be presented in D2.2 Human Machine Interface and Envelope, D2.3 Pilot training considerations for the implementation of a digital assistant and D4.3 Technologies roadmap).

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1. Executive summary

This document corresponds to the D1.1 deliverable "State of the art of cognitive computing algorithms" within the first work package of the HARVIS project. The purpose of this document is to stablish a baseline in order to develop the roadmap in how Cognitive Computing (CC) Algorithms could support the decision making of single pilot in complex situation, which is the main goal of this project.

Therefore, an assessment of the future aerospace sector has been carried out, considering future systems and tasks as well as human factor. Additionally, a state-of-the-art review in machine learning and cognitive computing algorithms and their integration into several sectors such as aerospace, automotive, healthcare, etc. has been made. Furthermore, a research of the different proposal for the implementation of the Single Pilot Operation (SPO) scenario has been done, analysing the different approaches and current regulations.

2. Introduction

2.1. Purpose and Scope of the document

This document aims at reporting the results of the state-of-the-art analysis carried out to develop a roadmap focusing on the creation of a virtual intelligent system able to help humans in a cockpit environment. Future aviation scenarios, single pilot operations, the use of artificial intelligence to develop a digital assistant, the human factors and the human-machine interface are some of the topics deeply analysed throughout this document.

2.2. Deliverable Structure

This document is structured as follows:

- Section 1 details the executive summary of the document.
- Section 2 summarizes the purpose and scope of this document as well as the structure it follows, and the acronyms and terminology used.
- Section 3 analyses the future aviation scenarios focusing on further systems, technologies, procedures, traffic, roles and human factors.
- Section 4 describes the necessary changes in the cockpit, from the point of view of tasks allocations and available supporting technologies, to allow single pilot operations.
- Section 5 presents an in-depth state-of-the-art analysis in the capabilities of Machine Learning and Cognitive Computing in a wide range of domains including aviation.
- Section 6 aims to evaluate which interfaces could facilitate a safe and proficient interaction human-machine.

2.3. Acronyms and Terminology

The following table reports the acronyms used in this deliverable.

Term	Definition
AI	Artificial Intelligence
ADS-B	Automatic Dependent Surveillance Broadcast
AMAN	Arrival MANager
AOCO	Airline Operational Centre Operator

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Term	Definition
AMAN	Arrival Manager
ASAS	Airborne Separation Assistance Systems
ASSAP	Airborne Surveillance and Separation Assurance Processing
ATC	Air Traffic Control
ATCO	Air Traffic Control Officer
ATM	Air Traffic Management
BoW	Bag of Words
BRLOS	Beyond Radio Line Of Sight
C2 link	Command and Control link
CAS	Complex adaptive socio-technical systems
CC	Cognitive Computing
CFMU	Central Flow Management Unit
CHMI	Cognitive Human Machine Interface
CIoV	Cognitive Internet of Vehicles
CNN	Convolutional Neural Network
CNS	Communications, Navigation and Surveillance
COGPIT	COGnitive cockPIT
COGMON	COGnition MONitor
CRM	Crew Resource Management
CSPO	Closely Spaced Parallel Operations
DERA	Defence Evaluation and Research Agency
DMAN	Departure MANager
DPM	Deformable Part Model

Term	Definition
DRML	Deep Region Multilabel Learning
EEG	Electro EncephaloGraphy
ETSO	European Technical Standard Orders
FAA	Federal Aviation Administration
FAR	Federal Aviation Regulations
FCS	Flight Control System
FCU	Flight Control Unit
FE	Feature Extraction
FER	Face Emotion Recognition
FMS	Flight Management System
FNIR	Functional Near InfraRed
GA SPO	General Aviation Single Pilot Operation
GA	Ground Associates
GAN	Generative Adversarial Network
GO	Ground Operator
GPS	Global Positioning System
GPs	Ground Pilots
GPWS	Ground Proximity Warning System
HF	Human Factors
HMI	Human Machine Interface
HMS	Human Machine System
HMT	Human Machine Teaming
HOG	Histogram of Oriented Gradients

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Term	Definition
HP	Human Performance
HPE	Human Performance Envelope
HR	Heart Rate
HRV	Heart Rate Variability
IAS	Intelligent Adaptive System
ICAO	International Civil Aviation Organization
ITP	In Trail Procedure
IVHM	Integrated Vehicle Health Management
LBP	Local Binary Patterns
LOAT	Level Of Automation Taxonomy
LSA	Latent Semantic Analysis
LSTM	Long-short Term Memory
MCDU	Multifunctional Control and Display Unit
MCP	Mode Control Panel
ME	Maximum Entropy
ML	Machine Learning
MTCD	Medium Term Conflict Detection
MTL	Multilabel Learning
NB	Naïve Bayes
ND	Navigation Display
NG-FMS	NextGeneration Flight Management System
NLP	Natural Language Processing
NMOC	Network Manager Operations Centre

Term	Definition
NMT	Neural Machine Translation
PACT	Pilot Authorization and Control of Tasks
PF	Pilot Flying
PFD	Primary Flight Display
PNF	Pilot Not Flying
RA	Resolution Advisory
RCO	Reduce Crew Operations
RCP	Required Communications Performance
RL	Reinforcement Learning
RLOS	Radio Line Of Sight
RNN	Recurrent Neural Network
RPAS	remotely piloted aircraft systems
SA	Sentiment Analysis
SA	Situation Awareness
SA&CA	Separation Assurance and Collision Avoidance
SASS	Situation ASSessor
SIFT	Scale-invariant Feature Transform
SPO	Single Pilot Operations
SRGAN	Super-resolution Generative Adversarial Network
STCA	Short Term Conflict Alert
SURF	Speeded Up Robust Features
SVD	Single Value Decomposition
SVM	Support Vector Machines

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Term	Definition
TA	Traffic Alert
TCAS	Traffic Collision Avoidance System
TCT	Tactical Controller Tool
TIM	Tasking Interface Manager
TRL	Technology Readiness Level
UAS	Unmanned Aircraft System
YOLO	You Only Look Once

Table 1: Acronyms

3. Future Aviation scenario

3.1. Future Systems

CleanSky pave the way of next generation cockpit systems and aircraft operations. The main areas of development concern large passenger aircraft, systems for green operations, airframe and systems. WP1 on avionics extended cockpit work(ed) on very large interactive head-down display, tactile interactive multifunction display and voice recognition integration in the cockpit. Other improvements were also carried out on new FMS functions like 'fly by trajectory', but also on an advanced modular surveillance system.

Avionics industrials like Thales, Rockwell Collins, Honeywell and Garmin are already working on new cockpits with larger and tactile displays, voice recognition systems, augmented reality and increasingly complex automation (see Figure 1).

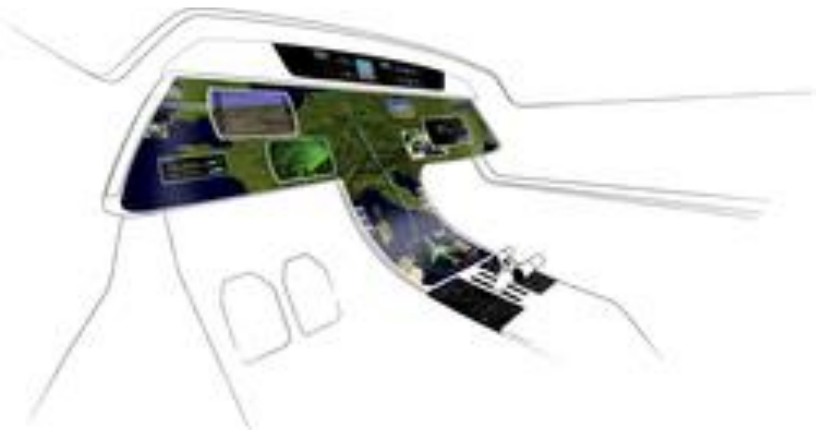

Figure 1. Thalès next gen cockpit © Thalès

Thalès next gen cockpit will include ASAS (Airborne Separation Assistance Systems), D-Taxi (Digital Taxi) via trajectory upload with datalink, 4D trajectories, Eco take-off on large multitouch displays.

In the future, aircraft will be more connected and huge quantity of data will have to be processed in order to give clear information to pilots and automations systems. Recent accidents shown that confusion can occur between the pilots and the state of automation, there are a lot of work to be done in order to help the pilot to better understand and interact with automation and recent research work is focused on giving feedback of pilot status to HMS.

The recent developments in artificial intelligence technologies could allow the machine to provide feedback and assistance based on the processing of various sources of information including models

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of human information processing, physiological measures of pilot state, natural language processing, speech recognition and vision. The purpose of such a system would be to support the pilot in the decision-making process by being able to adapt itself when goals and requirements evolve, interact easily with their human counterpart, identify and extract relevant elements on the situation including sensory inputs (vision, sound, gestures, physiological sensors). This new approach could help the pilot to maintain an optimal situation awareness (SA). The fields of neuroergonomics [1] and augmented cognition [2] rely on psychophysiological measurements in order to determine the user's cognitive state that could be used in intelligent adaptive systems (IAS).

3.2. Future pilots' tasks

As Next Generation Air Transportation System (NextGen) concepts change radically air traffic management, tasks, roles and responsibilities for the flight crew will evolve dramatically. Future flight deck will have available more complex and accurate information combined with new automation tools.

With more perspective, the role of pilot can be defined as a pilot or as a manager [3]. If the pilot keeps its role as pilot, he will still have the ability to control the aircraft, delegating tasks to automation. If the pilot become a manager, automation is responsible for the majority of aircraft control and navigation tasks, as well as the information processing tasks. Regardless of the evolution of the pilot role, its tasks and responsibilities will change.

Pilot of transoceanic flights will have new opportunities to reach more easily their optimal flight level. Over the ocean, without radar coverage, In-Trail Procedures (ITP) enable aircraft to change flight level to optimize fuel consumption. Where previously the separation was 80 to 100 nautical miles, ADS-B, GPS and other navigation sensors could divide it by up to 3 and the pilot could decide in this condition to avoid potentially-blocking aircraft. In addition to fuel savings, the benefit of ITP through ADS-B could be the improvement of pilots' situational awareness. The different traffic view will help the pilot to have a better understanding of the surrounding airspace.

Closely Spaced Parallel Operations (CSPO) with the use of more data (wake, weather, trajectory prediction) could enable paired approaches to minimum runway spacing in instrument meteorological conditions with the appropriate safety level [4]. This new technology is designed with consideration of the pilot capabilities. CSPO will transfer the responsibility for separation from the air traffic controller to the pilot in the flight deck.

Flight Deck Interval Management (FIM) is expected to enable air traffic controllers and pilots to increase runway capacity by reducing the uncertainty of time of arrival within 5 to 10 seconds. To make this possible, the concept propose that a pilot could have access to a "leader" aircraft speed given by the air traffic controller. This information will be used to define the safety distance between both aircraft and will increase the runway capacity. The systems may have an impact on the role and tasks of pilots and air traffic controllers since the separation is delegated to the pilot.

The number of clearances given by controllers will probably increase faster than the traffic itself. This will saturate VHF radio networks, and this is what motivates the use of Controller Pilot Data Link Communication (CPDLC). Reducing voice communication will potentially reduce pilot's situation awareness about aircraft in their vicinity. Boehm-Davis, in [5], confirmed that not only the pilot SA decrease, but the workload could also increase.

4. Single-Pilot Operations

4.1. Justification

For the last 10 years, there has been growing research in a concept known as Single Pilot Operations (SPO), which is focused on reducing the commercial cockpit to a single pilot from the current crew of two pilots. Recent advances in Communications, Navigation, Surveillance/Air Traffic Management and Avionics (CNS+A) technologies have allowed higher levels of automation, creating an opportunity for commercial airliners to transit to SPO. NASA Ames and NASA Langley have spearheaded this effort in the United States [6], but DARPA is also interested in this problem [7]. Additionally, many researches within the European Community have been carried out in order to address this possibility [8].

SPO may be regarded as the next phase of a decades-long downward trend in the minimum number of cockpit crew required for safe operations. In the 1950s, commercial aircraft typically had five cockpit crewmembers: captain, first officer (co-pilot), flight engineer, navigator, and radio operator. Advances in voice communication equipment removed the need for a dedicated radio operator position. Next, advances in navigation equipment (e.g., inertial navigation systems) removed the need for a dedicated navigator position. Finally, advances in engines, aircraft systems and improved tools for monitoring have removed the need for a dedicated flight engineer position.

Over the past 25 years or so, commercial aircraft have operated with a two-person cockpit (captain and first officer). It is important to note that the functions associated with the radio operator, navigator, and flight engineer positions did not simply disappear, they are now performed by the captain and/or first officer, assisted by cockpit equipment that has greatly reduced the human workload originally required to perform those functions.

Despite these advances, the transition from a two-pilot cockpit to a single-pilot cockpit will be significantly more challenging. A key requirement of SPO is to maintain safety at a level no lower than current two-pilot operations by the introduction of advanced cockpit automation and possibly new ground operator positions using support tools and air-ground communication links. The FAA's stance is that there is no apparent safety benefit to be gained from single-pilot operations, largely driven by the risk of pilot incapacitation. Such occurrences are very rare but do occur and how to ensure safe operation in this case will be a significant hurdle in any SPO future approvals [9].

While the safety issues for SPO are still to be fully addressed, the economic case for SPO is clear. There is a projected increasing pilot shortage through 2022, although the demand will likely be more in Asia and the Middle East [10]. The cost associated with crews (salaries, benefits, training, etc.) is a significant fraction of the aircraft operating cost, especially for operators that typically fly smaller aircraft with fewer seats than major airline operators that fly lager aircraft. That is why, crew cost and availability issues provide the motivation to explore the feasibility of safely operating long-haul and military operations with a reduced crew, and commercial aircraft with a single pilot in the cockpit

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assisted by advanced onboard automation and ground operators providing flight support services well beyond those currently delivered by aircraft dispatchers.

To address these issues, projects such as the Advanced Cockpit for Reduction of Stress and Workload (ACROSS) [11], Aircrew Labour In-Cockpit Automation System (ALIAS) [7] and the studies on SPO feasibility conducted by NASA under its Airspace System Program [9], have brought together academic, industrial and government organizations to develop solutions for workload reduction in the cockpit. These projects have prompted in the development of several concept of operations that covers the roles and responsibilities of the principal human operators, as well as many architectures for the automation tools used by humans and the operating procedures for human-human and human-automation interactions. The key points of these proposals are that they have been constructed using insights gained from a variety of sources including subject matter experts, human-in-the-loop experiments examining the performance these concepts of operations and cost-benefit analyses.

With the Captain as the only physical human presence in the cockpit, several theories for future SPO operations posit that many co-pilot functions will need to migrate to a ground control station. Indeed, research is underway investigating ground control strategies for remote assistance [6], [12]. Another theory is that significant improvements need to be made in automating the co-pilot's functions on board the aircraft, instead of shifting them externally. A derivative proposed architecture has one pilot in the highly automated cockpit, with onboard personnel serving as a back-up pilot, such as commuting pilots, flight attendants, and flight marshals [9].

Regardless of what such a resultant SPO architecture would look like, it is widely accepted that automation will have to substantially increase in the air and on the ground for such a SPO concept to be successful [6], [9]. To this end, substantial co-pilot functions, and even possibly functions currently assigned to the Captain, will be automated in the future. In the following subsections, a summary of the most remarkable proposals found in the reviewed literature is presented, which mostly coincide that the solution should incorporate knowledge-based capabilities as well as cognitive and adaptive interfaces to mitigate pilot's workload and improve situational awareness. These are relatively new concepts in civil aviation but are essential for the introduction of SPO.

4.2. Requirements and considerations for SPO

4.2.1. Systems requirements

Many researches have been conducted to assess the performance and safety changes to reduce crew and SPO in a present-say flight deck design. [13] highlights that Reduced Crew Operations (RCO) and SPO, using the current technologies and organization, significantly decrements flight performance, due to checklist are often sacrificed, more errors are committed, worse flight path performance, etc.; which leads to unacceptable safety margin. [14] underline that nonverbal communications are an important aspect of crew coordination and must be maintained or replaced to promote good awareness and Crew Resource Management (CRM) in SPO scenario. Furthermore, in [15] an interview with several pilots is conducted and they all agree that *"Going from two to one pilots is actually a subject we discuss frequently in the cockpit, and the nearly universal opinion (at this time) is that we can see a cockpit with only one pilot (although certainly not with current systems in use)..."*. At the end of this paper it is proposed a list of 12 functions that an onboard intelligent system should be able to replicate for a single human pilot to be able to manage the workload in piloting an aircraft in transport missions.

As regards to airworthiness directive, AMC 25.1523 requires that the aircraft flight deck design must be compatible with the workload allocated to the minimum Flight crew. To be noticed that in FAR 23 amdt 64 and CS 23 amdt 5, the notion of minimum flight crew does no longer appear, its definition is left to the applicant decision and ability to show compliance. In this sense, for SPO scenario become a reality, it will be necessary to work on these two aspects, for example by: decreasing pilot workload and flight deck complexity, increasing aircraft surveillance capacity, and facilitating collaborative work and information sharing between the aircraft, air traffic control, and ground crews; are some considerations extracted from [16].

- "Decrease pilot workload by taking control of certain flight tasks, including: improving communication and navigation tasks using Next Generation Flight Management System (NG-FMS); system monitoring through Integrated Vehicle Health Management (IVHM) and Avionics Based Integrity Augmentation (ABIA) systems, with the capability to issue cautions and warnings to the pilot when required and the ability to temporarily assume control authority in the event of pilot incapacitation." [16].

- "Decrease flight deck complexity with the integration of more automated tasks organised in different levels. This can be achieved by the use of adaptive interfaces which suggest appropriate automation modes based on task complexity and pilot workload; or using aural, visual and haptic alerts triggered by priority to avoid pilot confusion." [16].

- "Increase aircraft surveillance capacity through advanced avionics systems including: a surveillance system which ensures autonomous separation assurance and collision avoidance (SA&CA) in non-controlled and controlled airspace [14]; a weather surveillance system, augmented by ground forecasts from an air-ground data link and autonomous strategic/tactical re-rerouting and conflict resolution." [16].

- "Facilitate collaborative work and information-sharing with the ground station through: a combination of direct Radio-Line-of-Sight (RLOS) and beyond Radio-Line-of-Sight (BRLOS) air-to-ground communication channels between ground crew and ATCo, supplemented by ground-to-ground channels for redundancy and load balancing; secure, reliable data links with variable bandwidth and latency performances depending on available timeframe and task requirements; transferral of control authority to GO in the event of pilot incapacitation." [16].

- Adaptive systems: several studies [17],[18] argue that while higher levels of automation are required to support future operations, the nature of automation needs to be user-centric and adaptive to the needs of the human user. Thus, these systems should be able to assess the context and needs of the user based on passive or implicit inputs, dynamically reconfiguring itself to provide the required support.

The reviewed literature highlights that SPO will move to one pilot monitoring the systems controlled by an AI algorithm and coordinating some tasks with the ground operators. Currently, both pilots require constant communication between them. However, within this context, most of the interactions on the flight deck are between a human and a written software. This does not wholly cancel the need for Crew Resource Management (CRM) since, in addition to the coordination between the pilot and air traffic control, ground crews, and potentially other aircraft; there must still be an interaction between the pilot and AI controlling the flight. This comes in the form of human machine teaming (HMT).

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The HMT must be designed in such a way to achieve results comparable to those observed in a successful CRM. This means that some human factors and key ergonomic elements should be considered for system design, such as: facility of learning and remembering key functions, efficiency and intuitiveness of using automated functions, and avoidance/reduction of pilot-induced errors. Thus, the AI system would need to learn, communicate, and correct deviations like a second crewmember would do.

4.2.2. Main challenges

Once the main requirements that must be considered for the SPO scenario have been identified, some considerations of the challenges that must be addressed in order to implement this concept of operation are shown below (extracted from [13]):

A. Operational concepts

"Distribution of workload between pilot-in-cockpit and ground crew, single-pilot resource management, communication procedures and processes, as well as pilot/crew training requirements are important issues. Two conceptually different, but complementary operational concepts are considered herein, in addition to the current-day two-crew complement:

a) Reduced Crew Operations (RCO):

In RCO, two human pilots are on-board the aircraft. However, during the cruise phase of flight, only one pilot is actively engaged in flying the aircraft. The resting pilot may, in fact, leave the cockpit or may be seated in their cockpit seat.

b) Single Pilot Operations (SPO):

The only pilot on-board the aircraft serves as the captain and pilot-in-command (PIC), making all decisions and performing actions pertaining to command of the flight. In the event that assistance is needed, a ground operator may be linked to the cockpit via digital datalink, video, and/or radio." [13].

B. Remote pilot assistance

"It is assumed that part-time or scheduled, periodic support from a ground operator is a necessary condition for SPO. Thus, a ground operator can handle multiple flights, and if dedicated support is necessary, dedicated assistants can be provided. This concept raises the issues caused by the lack of initial situational awareness (SA) of a ground operator, when specialized assistance is requested. The conclusions of [19] highlight that, with appropriate displays, ground operators were able to provide immediate assistance, even if they had minimal SA prior to getting a request during in-route scenarios. The design of the ground station, the information, and the security and content of the datalink as well as the expertise of the ground operator are critical issues. NASA has been conducting research into remote pilot assistance, developing various operational paradigms (e.g., "Harbor pilot" or "Super Dispatcher") and most importantly, exploring whether a remote pilot can effectively complete the tasking and reduce the workload to safely enable SPO." [13].

C. **Pilot Incapacitation**

In-flight medical incapacitation is defined as a condition in which a flight crewmember was unable to perform any flight duties and impairment as a condition in which a crewmember could perform limited flight duties, even though performance may have been degraded [20].

Thus, the measurement of the pilot's psycho-physiological state and identification of adverse human physical and cognitive impairment will be crucial technology for RCO/SPO. The development of psycho-physiological measures, fatigue and state identification technologies are on-going [21] to meet the challenges of:

a) Developing sensor suites with appropriate data fusion methods since the results to date suggest that multiple sensor modalities are needed for most classifications.

b) Creating measurement and identification technologies that are robust and reliable enough to match the appropriate performance standards of nowadays onboard avionics systems (i.e., FAA Advisory Circular AC 25-1309).

c) Meeting these technology goals while simultaneously not over-encumbering the pilot, interfering with their operations on the flight deck, or violating privacy concerns.

D. Increasingly autonomous systems (IAS)

"New automation or more aptly, IAS, must perform or assist in the performance of functions that the second pilot in RCO/SPO flight would normally do. This does not necessarily mean relegating the RCO or SPO pilot to the pilot-monitoring role; the roles and functions for IAS must be tailored to the operation and the needs of the human. IAS are envisioned as intelligent machines (hardware and software systems) seamlessly integrated with humans, whereby task performance of the combined system is significantly greater than the individual components.

IAS utilize machine learning concepts and cognitive computing algorithms to perform functions without explicitly being programmed. These systems have the ability to modify and adapt their behaviour in response to their external environment and conditions. Nevertheless, these IAS are also designed using human-autonomy and automation interaction teaming principals. IAS, if properly designed, can replicate and in fact should enhance safety and reliability [22] (e.g., provide the ability to adapt to changing patterns and preferences; remain vigilant at all times; tailor automation actions to specific circumstances/add flexibility; increase situation awareness by context-sensitive information; monitor human actions and alert or intervene to prevent errors; improve automation ability to react quickly to avoid critical situations)." [13].

E. Technical and Communications

Since SPO will increase air-ground communications and impact in the actual CRM paradigm for both normal and abnormal conditions, it will be necessary to face these technical challenges by developing: High bandwidth and low latency communications (line-of-sight and beyond-line-of-sight data links for air-to-air, air-to-ground as well as ground-to-ground systems), autonomous navigation systems (flight planning, management, negotiation and validation), autonomous surveillance systems (sense-and-avoid, health monitoring), as well as, adaptive automation and interfaces for pilot and ground crew.

F. Safety

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Increase system integrity and performance, as well as assess the impact of higher levels of automation on flight safety and specify incapacitation procedures. Developing an Integrated Vehicle Health Management (IVHM) subsystem to monitor aircraft systems, providing appropriate updates, warnings or alerts; or increasing aircraft surveillance capacity to ensure autonomous separation assurance and collision avoidance, would be some goals to follow.

By creating these associated technologies and ensuring the proper human-autonomy teaming, the unique abilities of intelligent machines and humans are leveraged to create levels of safety and performance above and beyond that each one could provide individually. Such a systems may be especially suited during off-nominal events or in conditions where less experienced or non-expert operators are involved.

G. Human factor

Develop automation tools in order to achieve HMT, by assessing pilot workload, maintaining ground operator and pilot's situational awareness, addressing single-pilot incapacitation, developing new CRM procedures for interactions between the pilot and ground operator, building automation trust, as well as designing appropriate human-machine interfaces and interactions.

4.3. Tasks allocation for SPO

This section presents a concept of operation for the SPO scenario, as well as some suggestions for function and task allocation among the aircraft crew and ground operators, which summaries all the approaches analysed in the literature.

Implementation of SPO involves a transition from the current paradigm of a Captain, First Officer, and Dispatcher team using conventional automation tools, to a new paradigm of a Captain and Ground Operator team interacting with advanced human-centred automation tools, which results in changes in the operational mode as well as in the responsibilities of relevant personnel.

This new paradigm requires an evolution of the system in aircraft management centres, giving rise to an evolution of the current Airline Operational Centre Operator (AOCO) role, as well as, the reallocation or introduction of new tasks and jobs such as the Ground Operator (GO) role, which is analogous to that of a Remotely Piloted Aircraft System (RPAS) ground operator.

In [19] is proposed a scenario in which the AOCO assists the pilot with strategic tasks such as dispatch, optimal route planning and coordination with ATCo while the GO assists the pilot with tactical or emergency tasks such as re-routing and conflict resolution. In case of PF incapacitation, the GO will perform duties similar to those of a RPAS operator executing an emergency mission egress (i.e., landing in minimum time) and the associated landing procedure in co-ordination with the ATCo. Figure 2 compares the tasks carried out by the pilots and ground operators under normal conditions with two pilots, as well as in SPO and in the case of RPAS.

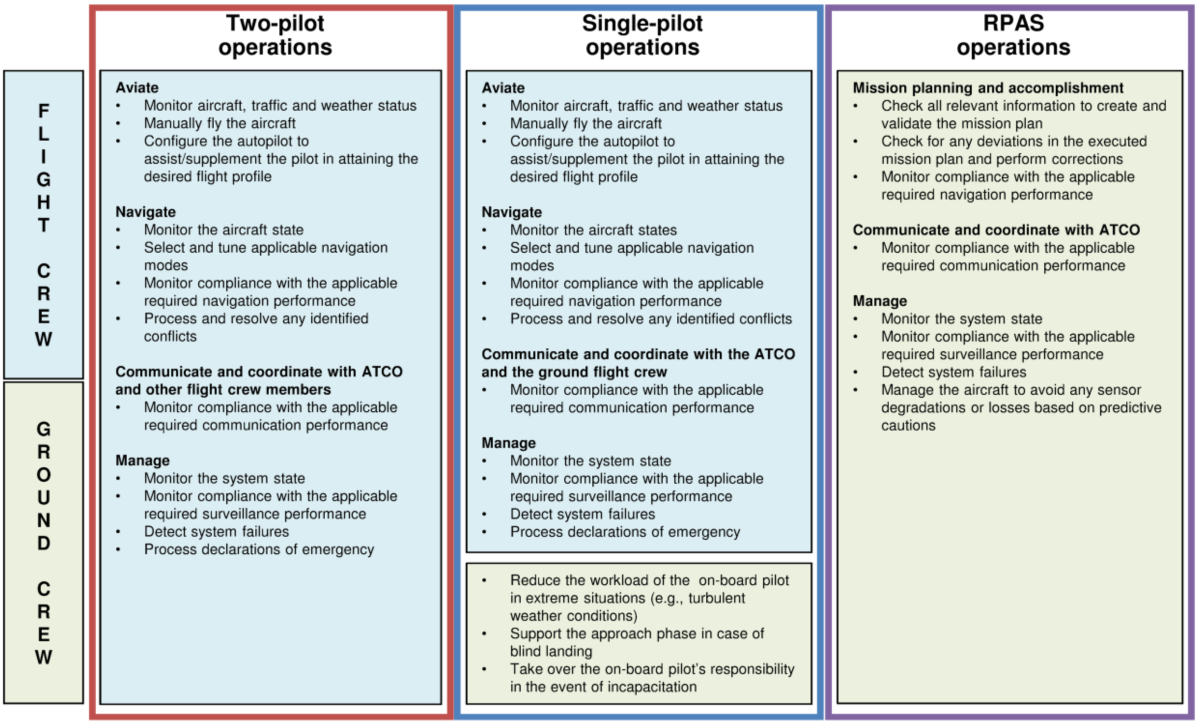

Figure 2. Piloting task analysis [16].

A first analysis of the concept of operations for SPO is introduced by [23], where it is exposed that the roles/responsibilities, tools, procedures, etc. will depend in part on the nature of the operating condition. This article proposes a taxonomy, Figure 3, based on the pilot's physiological and behavioural condition (normal vs. incapacitated) and flight condition (nominal vs. off-nominal). It is noted that the term "flight condition" refers to the myriad factors affecting the flight other than the pilot's condition, such as the status of aircraft systems, weather conditions, and airport availability.

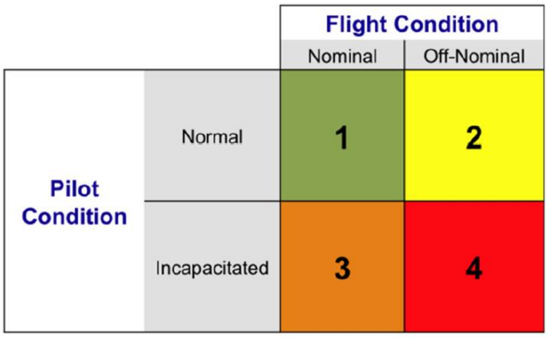

Figure 3. A taxonomy of operating conditions for SPO [23].

As the taxonomy condition (TC) progresses from 1 to 4, the operating conditions become more challenging, and the requirements for safe implementation of SPO become more complex. For example, in TC–1, there may not be much need for ground operator assistance; the cockpit automation could provide most of the assistance needed by the captain. In TC–4 the ground operator, acting as captain, may need assistance from other ground operators to land the aircraft. This issue will be a key driver in order to lay out the safety, reliability and redundancy technologically requirements for cockpit automation, remote flight-control tools for the ground operator, and air/ground data links.

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In the following subsections, the concept of operation system architecture for SPO scenario will be discussed in depth. It has been differentiated in two large blocks. The first block (4.3.1) focuses on the tasks performed by humans and the second one (4.3.2) address the advanced human-centred automation tools mentioned before and introduce the concept of Virtual Pilot Assistant (VPA), which is discussed on section 8.

4.3.1. Human Operations

This subsection summarizes some considerations for function allocation among the human operators on the aircraft and ground, discussed in [23]. In the following lines, characteristics of functions performed by the captain and ground operators are described; this includes options for organization structures for ground operators. The material presented in this section is not intended to be an all-encompassing treatment of RSO/SPO options for function allocation among human operators; its scope is limited to the options being considered by NASA in its ongoing development of a concept of operations for SPO.

4.3.1.1. Captain

“The captain is the final decision-maker regarding the flight mission, and (according to procedures) calls on automation and ground operator assets to accomplish this mission. Thus, unless incapacitated, she/he serves as the pilot-in-command (PIC), making all decisions pertaining to command of the flight. The captain’s main tasks are to manage risk and resources (both human and automation).

Under SPO scenario, the fundamental command/leadership role of the captain will not change, but the individual tasks and duties of the Captain will change significantly. The captain will likely take on some of the conventional Pilot Flying (PF) and Pilot Not Flying (PNF) duties, while other PF and PNF duties are allocated to the automation or the ground operators. The characteristics of the resources available to the captain will also be quite different, e.g., no first officer in cockpit, expanded menu of resources available from ground operators, new/advanced automation available in the cockpit. With this change in function allocation, a new CRM model will likely be required under SPO.” [23]

4.3.1.2. Ground Operators

“In current operations, flights receive ground support services from their Airline Operations Centre (AOC). Figure 4 depicts key positions in a typical AOC, which is supervised by an operation manager. There are various AOC teams that provide specialized services, e.g., dispatch, ATC coordination, crew scheduling, maintenance operations, customer service, and weather operations. It is anticipated that SPO would primarily affect the functions of the dispatch operations, with limited impact on other AOC services.

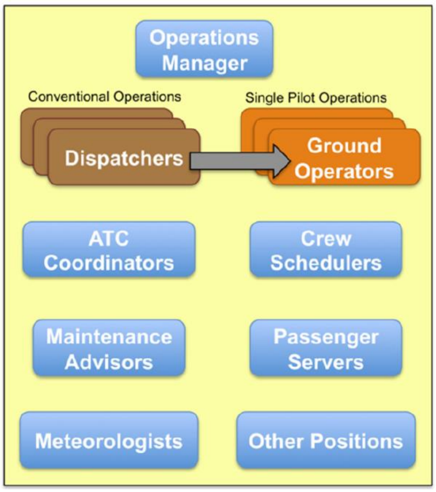

Figure 4. Representative layout of AOC [23].

In current operations, each dispatcher serves around 20 aircraft that are in various phases of flight at different locations around the country or even the world. A significant part of the dispatcher's duties lies in the pre-flight phase, where the dispatcher consults with the captain and uses various AOC tools to develop a flight plan (e.g., routing, cruise altitude, airspeed), determine fuel loading, meet weight and balance requirements, and ensure compliance with the minimum equipment list (MEL). After the dispatcher and captain sign the flight release, the dispatch functions transition to flight monitoring and serving as a conduit for information between the aircraft and other AOC operations. The dispatcher also plays an active role supporting the cockpit crew during off-nominal conditions such as aircraft equipment malfunctions, diversions to a different destination airport, and large (> 100 nmi) changes in routing. Dispatchers generally serve their flights all the way from pre-flight planning to gate arrival.

In SPO, certified dispatchers become ground operators (see Figure 4) who collectively perform conventional dispatch functions as well as piloting support functions, although each ground operator may not necessarily perform both functions. Ground operator teams will collectively perform the following three core functions: (1) Conventional Dispatch of multiple aircraft; (2) Distributed Piloting support of multiple nominal aircraft; (3) Dedicated Piloting support of a single off-nominal aircraft.

The **Conventional Dispatch** function has been described above.

The **Distributed Piloting** function corresponds to basic/routine piloting support tasks such as reading a checklist, conducting cross-checks, diagnosing an aircraft system caution light, etc. It is presumed that a single ground operator can provide such services to multiple aircraft because these non-urgent and relatively brief tasks can be prioritized and executed sequentially, and that little or no specialized training would be required if the distributed piloting function was performed by a dispatcher who has been certified for the aircraft type. This function would be applicable only to nominal aircraft, corresponding to Taxonomy Condition 1 defined in Figure 3.

The **Dedicated Piloting** function corresponds to sustained one-on-one piloting support requested by the captain under high-workload or challenging off-nominal operating conditions such as an engine fire, cabin depressurization, or diversion to an alternate airport due to low fuel and/or bad weather, etc. This function is also applicable to situations where the ground operator has to take command of an aircraft whose captain has become incapacitated. The tasks associated with this function may include flying the aircraft, e.g., remote manipulation of the aircraft's flight management system (FMS)

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for route amendments, or remote manipulation of the aircraft's Mode Control Panel (MCP) for sending speed/altitude/heading commands to the autopilot. The Dedicated Piloting function would be applicable to Taxonomy Conditions 2, 3, and 4 defined in Figure 3. The skills and training required to perform the dedicated piloting support function are essentially the same as those of a conventional pilot. One possibility is a rotating schedule where a pilot is scheduled for several weeks of airborne (cockpit) assignments followed by a week of ground (AOC) assignments. However, depending on the ground operator unit structure employed (see Figure 5), the pilot may need additional training in dispatch operations." [23].

Although safe operation is the primary concern, another point to consider in order to develop a structure for organised ground operations, are the operating costs. Some of these cost factors are: number of ground operators relative to the number of aircraft they can safely support, training/qualification requirements for those ground operators, the number of ground stations that require complex and reliable (and hence expensive) equipment such as that required to remotely control an aircraft's flight-path. Within this context [23] propose two ground operator organization structures of interest, **hybrid ground operator unit** (where all operators can perform any task) and **specialist ground operator unit** (where each operator performs a specific task), which are described below and illustrated in Figure 5. These ground operator organization structures have been selected by NASA, based on subject matter expert opinion, for evaluation in an upcoming human-in-the-loop evaluation.

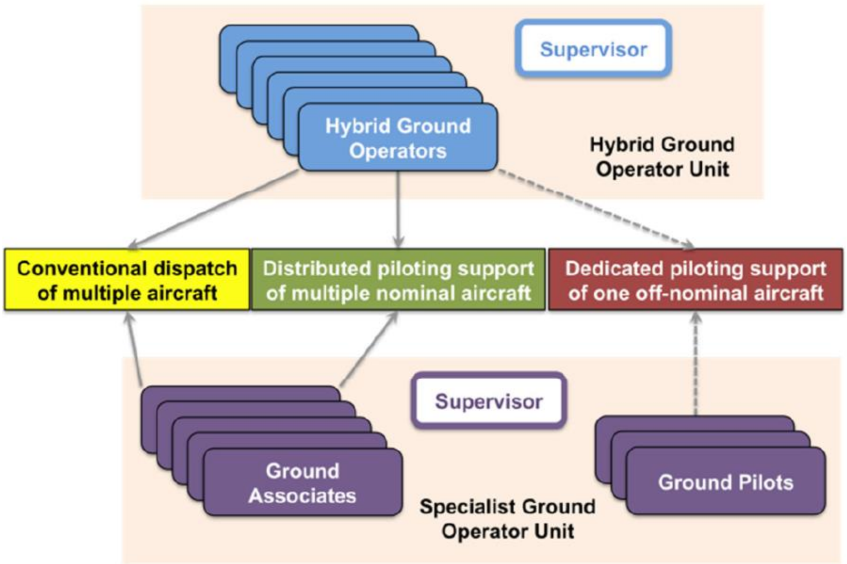

Figure 5. Examples of ground operator unit structures [23].

4.3.1.2.1. Hybrid Ground Operator Unit

"In this organizational unit, each hybrid ground operator (HGO) is trained and certified to perform all three core functions: Conventional Dispatch tasks, as well as Distributed Piloting and Dedicated Piloting support tasks. Each HGO generally serves multiple flights from pre-flight planning to gate arrival. However, if/when one of these flights encounters an off-nominal condition that requires dedicated support, the other aircraft are handed off to several other HGOs under the direction of the unit's supervisor. These handoffs will require some briefing given that most dispatch operators monitor and aircraft from preplanning to gate arrival. A more extensive briefing will be required if the involved aircraft needs special handling instructions. The HGO then provides one-on-one support to the off-nominal aircraft, calling upon other AOC positions (e.g., maintenance advisors) as necessary. After the off-nominal situation is satisfactorily resolved, the aircraft previously handed off by this HGO are returned to him/her if they have not already landed." [23]

4.3.1.2.2. Specialist Ground Operator Unit

"In this organizational unit, there are two types of members. Ground Associates (GAs) are trained and certified to perform tasks associated with Conventional Dispatch and Distributed Piloting support for nominal aircraft. Ground Pilots (GPs) are trained and certified to perform tasks associated with Dedicated Piloting support for off-nominal aircraft. There would be many more GAs than GPs in these units.

Each GA generally serves multiple flights from pre-flight planning to gate arrival. However, if/when one of these flights encounters an off-nominal condition that requires dedicated support that aircraft is handed off to a GP identified by a supervisor. Prior to the handoff, the GP may be on standby or performing collateral duties and would need a handoff briefing from the GA who was serving the off-nominal aircraft. The GP provides one-on-one support to the off-nominal aircraft. The GA maintains general situational awareness of the off-nominal flight in case the GP requires dispatch support or any other AOC support. After the off-nominal situation is satisfactorily resolved, the GP returns the aircraft (if it has not already landed) back to the GA." [23]

4.3.1.2.3. Harbour Pilot

"A harbour pilot is a type of ground operator serving as a member of a hybrid unit or a specialist unit (or any other type of ground operator unit). The function of a harbour pilot is similar to current practice in maritime operations. For example, there could be a harbour pilot with comprehensive knowledge of the Metroplex airspace in a concrete zone. Each harbour pilot provides distributed piloting support to individual nominal aircraft as they climb and descend through a complex terminal area airspace. This could reduce the workload of other positions in the ground operator units, enabling each position to support more aircraft." [23]

4.3.2. Human-Automation function allocation

This section presents some considerations for allocating functions between human operators and automation in SPO scenario. As mention before, in SPO the captain (in the cockpit) and ground operators (in an operations support centre), working as a team, will interact with advanced automation tools (located on the cockpit and in a ground station) to maintain flight safety and efficiency. Some of the simplest functions currently performed by a human pilot in a two-person cockpit, such as reading checklists and conducting cross-checks, are good candidates for automation, although such systems will have to possess some of the same characteristics as the operator they are replacing. Highly complex functions, such as formulating options to address challenging off-nominal flight conditions, are likely best suited to human cognition given the current state of automation sophistication and reliability. Other functions could be performed by humans assisted by various levels of automation. Higher levels of automation will generally require fewer human ground operators to service a given fleet of aircraft. It is likely that there will be a progression, along the SPO implementation timeline,

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from a larger ground operator complement using lower levels of automation to a smaller ground operator complement using higher levels of automation.

Many previous researches (ACROSS) [11] and (ALIAS) [7], suggest that this new human centred advanced automation tools should incorporate knowledge-based capabilities as well as cognitive and adaptive interfaces to mitigate pilot's workload. These are relatively new concepts in civil aviation but are essential for the introduction of SPO. Considering both, the SPO concept of operations and the evolving regulatory framework for conventional, general aviation and unmanned operations, the system architecture for a certifiable Virtual Pilot Assistant (VPA) is proposed in several studies, as a key to enable the implementation of SPO for commercial airliners. The VPA is a knowledge-based system, which reduces single-pilot workload in the cockpit through increased system autonomy and closer collaboration with the ground component.

In the following subsection it is summarized the approach carried out by [16], which discusses the integration of Communications, Navigation and Surveillance (CNS) systems with the VPA and introduces the concept of a novel cognitive Human Machine Interface (CHMI) [24], which provides a real-time estimation of the pilot's cognitive states for adaptive alerting and task allocation.

4.4. Certification and Normative

There are no operational regulations allowing SPO for commercial aviation at this point. However, there is ample literature covering conventional two-pilot operations, GA SPO as well as remotely piloted aircraft systems (RPAS), which can be assumed as the basis for the development of commercial SPO certification standards.

In terms of airworthiness certification standards, current European and Federal Aviation Regulations (CS/FAR) Parts 25, in particular CS/FAR 25.1523 and Appendix D do not explicitly exclude SPO. According to them, the criteria for deciding minimum flight crew are based on pilot workload and flight safety when a pilot is incapacitated; to achieve certification, SPO needs to show that pilot workload remains at an acceptable level during normal/emergency operations, and that pilot incapacitation does not compromise flight safety.

Unlike airworthiness, the operational requirements for commercial air transport described in the EU Air OPS (EU) 965/2012 Part ORO-FC-200 as well as in FAR 121.385(c), require a minimum of two pilots for commercial operations. Whereas ICAO standards for air operators i.e. Annex 6 – 9.1 on Composition of the Flight and 9.4.5 on Single pilot Operations under the IFR or at Night do not explicitly require Two pilots for Commercial Air Transportation and do not limit the single pilot operations under IFR to turboprops with less than 9 passenger seats .

The following section provides a review of current certifications extracted from [16]. Within this review, Acceptable Means of Compliance (AMC), Guidance Materials (GM) and recommended practices applicable to SPO are presented. The material is sourced from national/international organizations such as the International Civil Aviation Organization (ICAO), Federal Aviation Authority (FAA), European Aviation Safety Agency (EASA), Civil Aviation Authorities (CAA) from Australia, the UK and New Zealand, the US Department of Defence (DOD) and the Institute for Defense Analyses (IDA). References are also made to standards from Aeronautical Radio Incorporated (ARINC), American Society of the International Association for Testing and Materials (ASTM), Radio Technical Commission for Aeronautics (RTCA), Society of Automotive Engineers (SAE), and NATO Standardization Agreements (STANAGs).

“For SPO, the main guidelines for crew responsibility and authority are described in CS/FAR 23.1523 (before amdt 5 & amdt 64 respectively), EU Air OPS Annex VIII Part-SPO (Special Operations), Subpart A (SPO.GEN.105/106/107). EASA's AMC/GM to Annex III provides additional guidelines for SPO personnel (SPO.100), high-risk commercial operations (SPO.110) and CRM training (FC.115). ICAO Annex 1, Section 2.1.3 provides recommendations for class and type ratings for single-pilot aircraft. EU Air OPS Part ORO.FC.202 provides requirements for Single-pilot operations under IFR or at night.

Section 9-11 to 9-17 of FAA-H-8083-9A gives an overview of Single-pilot Resource Management (SRM); FAA AC 91-73B provides guidelines for taxi procedures for Part 91 and 135 SPO; CASA EX43/11 provides an exemption for SPO in Cessna 550/560 aircraft along with accompanying requirements and conditions; CAA AC 91-11 is an advisory circular for SPO under IFR rules containing the relevant checklists, CRM guidelines, and outline of a typical SPO flight; CAA Standards Document 14 provides guidance for the required skill tests and proficiency checks in the certification and licensing of SPO aircraft.

- **Technical Aspects:**

Technical considerations capture the requirements and recommendations for the design and development of CNS systems. There are no specific technical requirements unique to SPO at this point, although some are embedded into two-pilot requirements (e.g., EASA Annex VIII, SPO.IDE.A.126, FAA AC 91-100(0) Sect. 6). Thus, some Requirements from two-pilot operation, as well as references covering aspects of the Command and Control (C2) link and sense-and-avoid functionalities from RPAS have been considered relevant for SPO scenario.

For two-pilot aircraft, the requirements for system design and installation are given under FAR 25, along with the communication (RTCA DO-238, ICAO 9869 AN/62), navigation (ICAO 9613 AN/937) and surveillance (RTCA DO-289, ICAO 9224) system requirements. For RPAS technical requirements, references are made to both civil and military domains. For civil aviation, Chapters 10 to 13 of ICAO’s Manual of RPAS makes technical recommendations for communications, surveillance and C2 systems. JARUS D.04 covers the required C2 link performance, Appendix C.3 of FAA’s roadmap covers the future technical requirements for integrating UAS into the civil airspace [25], including ground-based/airborne sense and avoid, as well as C2 and interoperability requirements; these are expected to be (or have already been) captured in European Technical Standard Orders (ETSO) and RTCA Minimum Operational Performance Standards (MOPS) referenced in its Appendix. CAP 722 provides some guidance on system autonomy, as well as sense-and-avoid. Military regulations for unmanned systems are specified in NATO’s STANAG 4586 and DOD’s Unmanned Systems Integrated Roadmap – the former defines the interoperability and HMI requirements for RPAS in NATO’s Joint Service Environment while the latter recommends research areas to achieve greater interoperability.

- **Safety Aspects:**

While there are no specific safety guidelines for SPO, the necessary requirements are similar to (and can be derived from) two-pilot and RPAS operations. The safety requirements for system design are extracted from CS/FAR 25.1309 and the corresponding EASA AMC and FAA Advisory Circular 25.1309 on showing compliance with fail-safe design. SAE provides Aerospace Recommended Practices for the development and design (ARP-4754A) and safety assessment (ARP-4761) of avionics systems. JARUS AMC RPAS.1309 provides a means of compliance for the safety and risk assessment of RPAS systems, also making reference to ARP-4754A, ARP-4761 and CAP-722. EUROCAE ER-010 accompanies RPAS.1309 and presents the safety objectives, risk assessment approach and guiding principles for safety/risk assessment. CAP 722 Section 4, Chapter 4 offers additional guidance for general safety assessment, and ICAO 10019 AN/507 Chapter 7 provides guidelines for safety management in the operational context

- **Human Factors Aspects:**

The human factors considerations provide a framework for interface and interaction design, system behaviour, crew resource management (CRM) and human-machine teaming. FAA TC-13/44 is a recent report by the FAA, comprehensively addressing the human factors considerations on the flight deck. These include the design and evaluation of: display formats; the organization and content of information elements; visual and auditory alerting, control/input devices; design philosophy and function; error management, prevention, detection and recovery; workload and automation. Requirements relative to "Installed systems and equipment for use by the flight crew" can be found in CS/FAR 25.1302, and guidance material on "the design and evaluation of controls, displays, system behaviour, and system integration, as well as design guidance for error management" can be found in EASA AMC and FAA AC 25.1302. . ARINC 837 goes into detail regarding design guidelines for cabin HMI. The SPO publications in this area are related to Single-pilot Resource Management (SRM) in GA-aircraft (CAAP 5.59-1(0)). For RPAS, CAP 722 provides an overview of the human factors issue in design, production, operations and maintenance. STANAG 4586, Appendix B3 provides the HMI requirements for interoperability within NATO operations, and Chapter 10 of the DOD Unmanned Systems Roadmap (11-S-3613) provides a discussion of past, present and future requirements of human-machine teaming with autonomous systems." [16].

5. Human Factors

Human are good at reasoning, interpretation and problem solving. Unlike machines, they are able to adapt to new problems for which no rules or procedures already exists. However, they are prone to well-known limitations with regards to information processing. Humans can remember a limited number of information and have difficulties to perceive changes in their environment due to limited detection and vigilance capabilities [26] .

For decades, in order to address those limitations, automation has been integrated in complex systems. In the cockpit, the first autopilot has been introduced in 1912, contextual alarms and modern flight management system where integrated in eighties. Since then, automation has been the only answer to flight management and human computer interaction in the cockpit. The main drawback of this approach is that automation do more than simplify tasks for pilots, **it also changes the nature of their tasks** and can lead to the out of the loop syndrome described by Endsley & Jones in [27] as a Situation Awareness enemy with Requisite Memory Trap, Workload, Anxiety, Fatigue, Data Overload, Misplaced Salience, Complexity Creep, Errant Mental Models.

The HARVIS project aims at considering also the Human Factors aspects of the introduction of a digital assistant in future cockpit. To do this, some **theoretical and methodological framework will be applied**:

- Look for the correct balance between humans and machines, selecting the right tasks to automate and the right level of automation, paragraph 5.1.
- Select the most appropriate level of automation considering the impact on safety and performance, paragraph 5.2.
- Understand which Human Factors will be most impacted in the new scenario, paragraph 5.3.
- Associate combination of Human Factors (e.g. specific levels of workload, attention, stress) to Human performance, paragraph 5.4.

These frameworks form the basis on which the Human-Machine partnership concept will be built on (in Deliverable D2.2- Human-Machine Interface and Envelope)

5.1. The interaction between automation and humans

As postulated in research by Sheridan & Verplanck in [28] automation is not all-or-nothing, that is, automation is not only a matter of either automating a task entirely or not, but **to decide on what task to automate and on the extent it should be automated.**

In fact, different tasks involve the use of different psychomotor and cognitive functions, which in turn implies the adoption of different automation solutions. For example, expanding human capabilities to monitor a certain process (e.g. a Remote Tower) is not the same as replacing the human in the execution of a certain action (e.g. the aircraft auto-braking system). Similarly supporting the analysis

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of a complex dataset, such as that involved in predicting the risk of a traffic conflict, is not the same as identifying the best solution to resolve the conflict.

Automation then **is not seen to replace operators but to empower them and to improve the overall performance of systems** as clearly defined in [29] the research network on Higher Automation Levels in Aviation (HALA!). This approach is similar to the one followed in the early 80's when flying crew for large civil aircraft was reduced from three to two by adding sophisticated Flight Management Systems (FMS) [30].

However, it is important to design this automation very carefully taking into account the elements of Complex adaptive socio-technical systems (CAS). As clearly pointed out by Lisanne Bainbridge in [31] automation malfunctions end up most of the time in the hands of operators that were precisely supported with automation as their tasks were too complex or too resource consuming. Moreover, introducing higher level of automation requires (beyond design issues) an evaluation of the impact which the new technology may have on each CAS part (operator, computing system and organisation) such as tasks migration and/or functions allocation [32].

On the top-right side of Figure 6, Air Traffic Controllers communicate with pilots via data link or transfer aircraft interacting on the electronic labels of the aircraft on the radar screen instead of using paper strips and communicating by voice using Very High Frequency medium.

Similarly, on the airborne side (lower part of Figure 6), glass cockpits [33] provide a means for integrating information to support pilots activities while this information was previously distributed amongst multiple displays throughout the cockpit.

In both cases, task migration and/or functions allocation require that humans improve their knowledge, learn how to interact and collaborate with the new technology for accomplishing tasks.

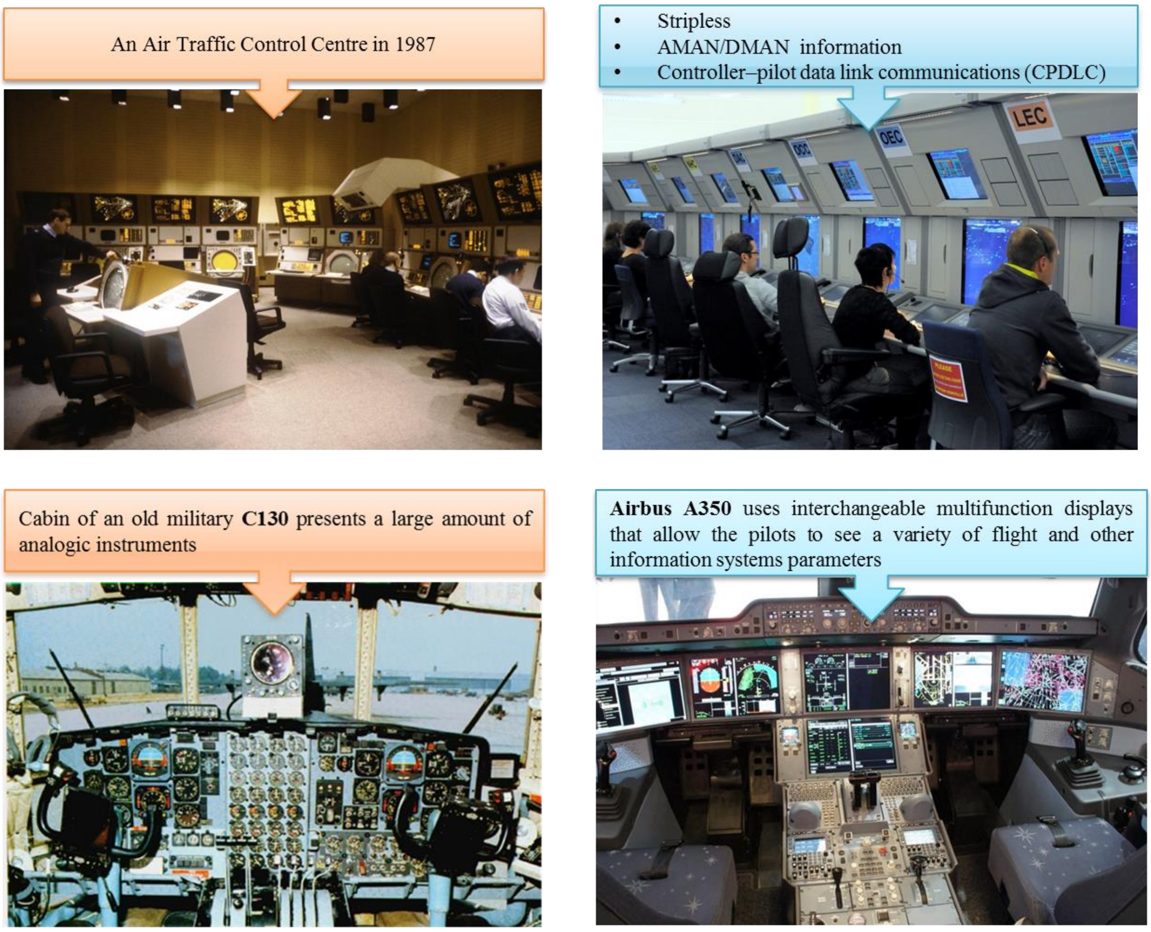

Figure 6: The enhancement of integrated automation support in ATCs and cockpits over time.

In automated systems, function allocation [34] between human and machine has always been a point of controversy. In the context of automation, "functions allocation" means that the actor (either human or machine) that is best suited (based on some continuum of parameters) should perform the function. The basis for selection and grading of such parameters is at the heart of the issue of function allocation and has been subject to much investigation over the years.

The selection of the HARVIS solution will be based on the selection of the right tasks to be automated (considering the future scenario described in the previous paragraphs) and a framework that considers the pros and cons of the delegation of them to the machine, looking for a safe and efficient balance. Such a framework has been already be applied in previous EU funded projects (NINA, STRESS) and is described in the next paragraph.

5.2. Levels of automation taxonomy

The approach proposed by Fitts with his Men are best at – Machines are best at (MABA-MABA) list [35], relied on the idea that, given a set of 44 pre-existing tasks, one should decide which ones are worth automating, considering the strengths and weaknesses of respectively humans and machines. Although this approach is now deemed outdated, there is still limited awareness of the fact that

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introducing automation brings qualitative shifts in the way people practice, rather than mere substitutions of pre-existing human tasks.

An initial scale of levels of automation was proposed by Sheridan & Verplanck in [28] representing a continuum of levels between low automation, in which the human performs the task manually, and full automation in which the computer is fully autonomous (see Figure 7).

Low	1	The computer offers no assistance, human must take all decisions and actions
	2	The computer offers a complete set of decision/action alternatives, or
	3	Narrows the selection down to a few, or
	4	Suggests one alternative, and
	5	Executes that suggestion if the human approves, or
	6	Allows the human a restricted veto time before automatic execution
	7	Executes automatically, then necessarily informs the human, and
	8	Informs the human only if asked, or
	9	Informs the human only if it, the computer, decides to
High	10	The computer decides everything, acts autonomously, ignores the human

Figure 7: Levels of Automation of Decision and Action Selection by Sheridan and Verplanck

A decisive step was made in [36] by Parasuraman et al. who acknowledged the Sheridan-Verplanck 10-point scale and introduced the idea of associating levels of automation to functions (Figure 8). These functions are based on a four-stage model of human information processing and can be translated into equivalent system functions:

(1) information acquisition,
(2) information analysis,
(3) decision and action selection and
(4) action implementation.

The four functions can provide an initial categorisation for types of tasks in which automation can support the human.

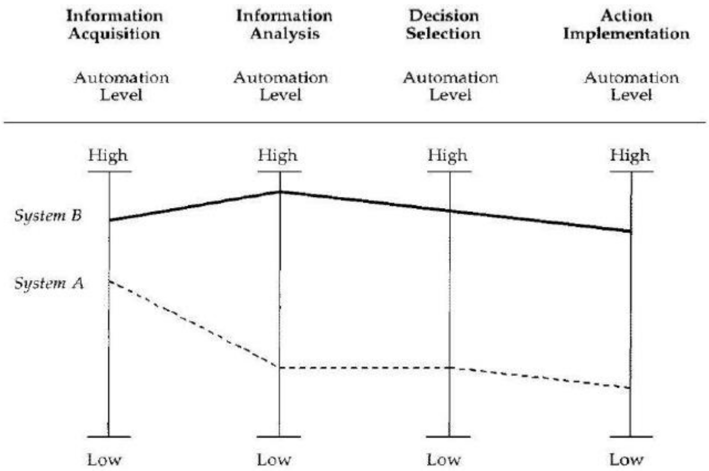

Figure 8: A model of types and levels of automation by Parasuraman et al.

Most of the time automation is only partial keeping the operators in the loop so that they can forecast what will happen next and interfere with automation in case of adverse events or automation malfunction. The design of this cooperation requires understanding how to balance automation and interactivity and specify how a task can be performed by assigning the generic functions to the operator and the system in terms of function allocation. "**Function allocation cannot be based on a consideration of the tasks only, but must consider the total equilibrium of a work situation—corresponding to a notion of balanced work.** The concept of equilibrium emphasises the fact that a change in function allocation disturbs the established equilibrium. This will have consequences for the system as a whole, and one result may be that a new equilibrium is established which differs significantly from the previous one."

Previous work on automation can be divided according to three different perspectives:

1) the design perspective which focuses on how to engineer the computing systems (offering automation) and more precisely its user interface [37];
2) the evaluation perspective which focuses on how to assess the operational aspects of automation including performance impact of automation on operations [38], [39];
3) the human perspective which focuses on how to understand the role of the operators who deal with a new technology or a different level of automation [38], [40]

While this research work has been mostly conducted in separate fields, as the increase of automation might come along with an increase of performance variability of the whole aviation system especially in case of new automated systems, there is a need to provide an integrated view on these disjoint research activities [41].

In the framework of the SESAR Programme, a **Level Of Automation Taxonomy (LOAT)** has been developed to classify and compare different kinds of automation support [40]. The LOAT (Figure 9) is based on the taxonomy of Endsley & Kaber and the principles of Parasuraman, which combines cognitive functions and levels of automation, and on ideas from activity theory and distributed cognition [42]. Its purpose is to classify automation examples in a practical way. The Taxonomy is organised as a matrix. In the horizontal direction, four functions are depicted: information acquisition, information analysis, decision and action selection, and action implementation. A consequence of having four functions – different in nature – is that each function can be automated at different levels. In line with this, vertically, each cognitive function groups a number of automation levels (between 5 and 8). All automation levels start with a default level 0, corresponding to manual task accomplishment, and increase to full automation. Automation level 1 is based on the principle that the human is accomplishing a task with primitive external support, which is not automation as such. Any non-automated means that support the human mind, e.g. using flight strips to compare parameters of different aircraft and to pre-plan future traffic, could correspond to this intermediate level.

The classification of the level of automation is provided according to the concerned cognitive function. This means that a certain technology may have different levels of automation according to whether we look at the information acquisition (A), information analysis (B), decision-making (C) or action implementation (D) fields. Examples of technologies are included in the LOAT, to facilitate the reader in understanding how to interpret and use the table for the classification of a technology. Figure 9 presents a simplified version of the LOAT. The full version is provided in Appendix A.

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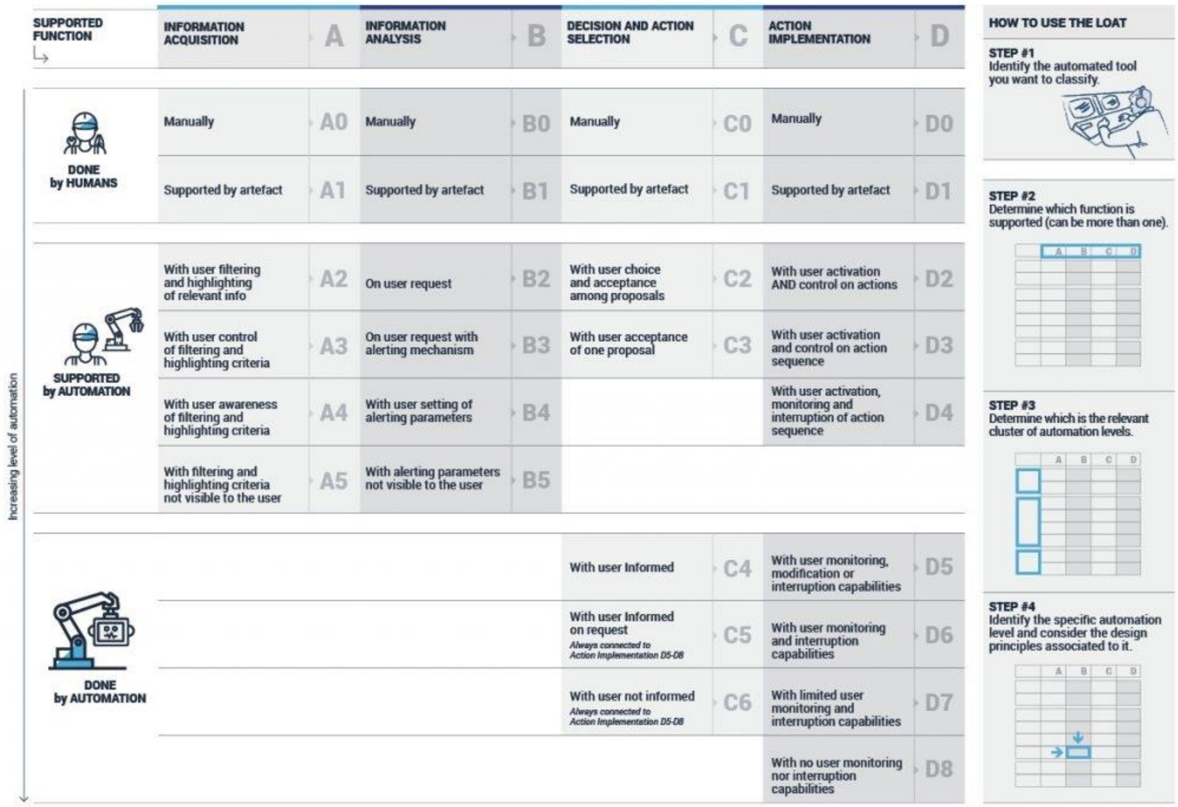

Figure 9: The LOAT (from dblue.it/projects/project-levels-automation-taxonomy)

The way LOAT is designed demonstrates the following principles [40]:

- An automated system cannot have one 'overall' level of automation as such. In other words, a statement about a level of automation for a system always refers to a specific function being supported;
- One automated system can support more than one function, each having a different level of automation;
- The description of each automation level follows the reasoning that automation is addressed in relation to human performance, i.e. the automation being analysed is not just a technical improvement but has an impact on how the human is supported in his/her task accomplishment.

It should be kept in mind that these generic functions are a simplification of the many components of human information processing. The functions are not meant to be understood as a strict sequence, but they may temporally overlap in their processing. From a practical point of view, the human may be performing a task that involves one or several functions. However, it is useful to differentiate the subtleties between the functions when one wants to identify how a specific automated system supports the human.

5.2.1. Automation support to ATCOs and pilots tasks

Pilot and Controller tasks are not automated in the same way [43]. Aircraft automation is sometimes considered to be more advanced than ATC automation. This perception is only partially true, as it seems to disregard the nature of pilot and controller activities, at least to the extent that non-pilots sometimes understand them. Pilot tasks are much more “Action Implementation” oriented than controller tasks, for which the emphasis is more on monitoring, planning and communicating. Therefore, the replacement or support of a human action – which is normally perceived as “real” automation – is inevitably more successful when pilot tasks are concerned.

In the limited number of automated functionalities reported as examples in the LOAT, there is a prevalence of “Information acquisition” and “Information Analysis” functions in ATC-related automations. Examples of this were the Multi-Radar Tracking system display, the Short Term Conflict Alert (STCA) system, the Medium Term Conflict Detection (MTCD) system and the Tactical Controller Tool (TCT). On the other hand there was a clear prevalence of “Action Implementation” functionalities among aircraft automations. For instance, the Autopilot following a FMS trajectory, the Autobrake system and the ASAS-ASPA (Airborne Separation Assistance – Airborne Spacing system) capability. Finally a more balanced distribution between ground and aircraft was observed for the “Decision and Action Selection” automations, although the ATC functionalities were generally less mature and were providing a lower level of support. The Arrival Manager (AMAN), which is a good example of ATC “Decision and Action Selection” functionality, is increasingly prevalent but in most of the cases it provides just a useful reference that the controller may decide to follow or not, depending on operational circumstances. This kind of support is at a considerably lower level than that offered, for example, by the Resolution Advisory (RA) of the Traffic Collision Avoidance System (TCAS) which indicates to the pilot one single and directed action to avoid possible collision with conflicting traffic.

It is interesting to note that some of the aircraft functionalities analysed also included “Information Acquisition” and “Information Analysis” components. However these were generally acknowledged to be less sophisticated than the ATC-related ones (consider the example of the TCAS Traffic Display which is known to be of limited functionality relative to controllers' radar displays and well known to be unusable by pilots as a means of self-separation). Much more sophisticated “Information Acquisition” functionalities are beginning to be introduced for the flight deck and we looked at ATSAW-SURF (Air Traffic Situation Awareness for Surface Operations) – which uses *Automatic Dependent Surveillance - Broadcast* (ADS-B) capability. More than just a simple technological improvement, this will, subject to the development of operator procedures, make possible a partial delegation to pilots of tasks which have previously been an exclusive prerogative of ATC.

5.3. HFs relevant concepts in future scenarios

Technological and organizational changes constantly bring about a practical need to know about the cognitive and emotional processes of the operators. Most of the proposed changes deriving from the implementation of the future scenario described in the previous paragraphs are expected to increase the pilot’s autonomy in controlling the route of their aircraft, including the requirement to maintain required separation between aircraft. Flight time, delays and fuel expenditures are all expected to profit from such changes.

The pilots’ role would be shifted from that of an active controller to one more like that of a monitor [44][45]. As systems become more automated, and humans move to monitoring positions, the weight of stress is likely to grow. A typical case is the automation disruptions, when humans have to react quickly in highly stressful conditions. In these cases, stress is known to influence performance and impair attention, memory, and decision making [46]. The relevance of stress is also recognised by EASA, that in the Notice of Proposed Amendment (NPA) addresses the issue of licensing and medical certification of air traffic controllers [47], considering stress and fatigue management as an essential topic for training (AMC1 ATCO.D.045(c)(4) Human Factors training).

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The HARVIS project will work on a solution what will not impact negatively pilots' cognitive state. Particular attention will be paid for those Human Factors which are more likely to be impacted when reduced crews have to interact with a partially autonomous system. In the following section a review of the frameworks for understanding these factors are provided.

5.3.1. Stress

According to psychological theories stress is determined by the balance between the perceived demands from the environment and the individual's resources to meet those demands [48], [49].

So stressful experiences arise as person-environment transactions. These transactions depend on the impact of the external stressor. This is mediated firstly by the person's appraisal of the stressor and secondly on the social and cultural resources at his or her disposal [50]. When faced with a stressor, a person evaluates the potential threat (primary appraisal). *Primary appraisal* is a person's judgment about the significance of an event as stressful, positive, controllable, challenging or irrelevant. Facing a stressor, the *second appraisal* follows, which is an assessment of people's coping resources and options. Secondary appraisals address what one can do about the situation. Actual *coping efforts* aimed at regulation of the problem give rise to *outcomes* of the coping process.

Lazarus has drawn a distinction among three kinds of stress: harm, threat, and challenge. Harm refers to psychological damage that had already been done, as for example an irrevocable loss. Threat is the anticipation of harm that has not yet taken place but may be imminent. Challenge results from difficult demands that we feel confident about overcoming by effectively mobilizing and deploying our coping resources. These different kinds of psychological stress states are presumably brought about by different antecedent conditions, both in the environment and within the person. They are relevant in the framework of our research as they can have different consequences in terms of human performance.

For example, threat is an unpleasant state of mind that may seriously block mental operations and impair functioning, while challenge is exhilarating and associated with expansive, often outstanding performance. To the extent that we take these variations seriously, stress cannot be considered in terms of a single dimension such as activation. The recognition of the different dimensions of stress involves considering diverse emotional states (some negative, some positive) and different impact on performance.

The model also highlights that the relation between stress and performance is not linear. In fact, stress is normal up to a point and can be optimal for certain performance related tasks, while it becomes a problem when interfering with a person's ability to do daily life tasks over a period of a few weeks or impacting his/her health in a dangerous or risky way. It has been seen that stress can influence performance and may impair attention and memory, and can contribute to an increase of human errors and accidents. In general, stress affects how we perceive and process information, as well as what decisions we make, leading to an increase in the number of errors and mistakes.

From a physiological view, a typical stress response means that autonomic activity increases, although in certain situations and in certain individual's the stress response might be different (even a decrease is possible). The basis of the physiological stress model has its roots in the research activity of Walter B. Cannon and later Hans Selye. Cannon [51] developed the "*fight-flight*" concept, which linked emotional expressions, such as fear, to physiological changes in the periphery. He emphasized the activation of the *Sympathetic Adrenal Medullary* (SAM) system in such situations, irrespective of whether the emergency reaction was "fight" or "flight". The more reactive biomarkers of the *fight-flight* response are the catecholamines, in the form of adrenaline and noradrenaline, which increase when stress appears, and other physiological indicators associated with the *Autonomic Nervous System* (ANS). Selye [52] theorized the *General Adaptation Syndrome* (GAS) to model the dynamic of the human body adaptation to stressful environmental conditions. Therefore, the SAM system is activated when the individual is challenged in its control of the environment, or is threatened, and this defence reaction prepares the body to battle or escape. Increased adrenaline under normal levels of stress is associated with improved performance. In fact, several studies show that stress, but only up to a certain level, improve performance, e.g. on selective attention tasks [53]. In fact, the cognitive psychology literature demonstrates that activation has an ‘‘inverted U-shape’’ relationship with performance in that some levels of activation may help an individual to perform at a level that is higher than their baseline state [54]. LeBlanc et al. (2008) noted that general surgery residents had improved technical performance on training tasks while dealing with stress conditions. On the other hand, excessive activation may lead to severe stress that overpowers an individual or team, with resulting impairment in memory, attention, decision-making, and general performance, regardless of previous training [46].

Therefore, stress is a physiological response to the mental, emotional, or physical challenges that we encounter. The immediate body's “fight or flight" response causes hormones secretion into the bloodstream to intensify concentration and quicken reflexes. From a physical point of view, several reactions related to the ANS activation can be measurable, such as increased heart rate skin sweating. Under healthy conditions, the body returns to its normal state after dealing with acute stressors.

Stress can be categorized into two basic forms: **acute stress**, relatively short in duration and is often experienced as caused by high task load; **chronic stress**, prolonged stress that can result from occupational or non-occupational sources. Four possible situations that may cause chronic stress: too frequent stress exposure, failure to habituate to repeated exposure of the same kind of stressor, inability to shut off the stress response, despite that stress has terminated, and situations that cause regulatory disturbances of the stress system.

Continuous monitoring of an individual's stress levels is essential for understanding and managing personal stress.

5.3.2. Attention

Attention is the ability to **attend to information** in the environment [55].

In particular, attention allows us to process selectively the vast amount of information whom we have to face, prioritizing some aspects of information while ignoring others by focusing on a certain location or aspect of the visual scene [56]. Attention can be classified into three main components:

- Selective attention: The ability to process or focus on one message in the presence of distracting information.
- Divided attention: The ability to process more than one message at a time.
- Visual attention: The mechanism determining what information is or is not extracted from our visual field.

One important concern for a notification system in the aviation field is that seemingly prominent objects in the visual field can sometimes elude attention despite their relevance and importance to the primary task [57]. This phenomenon “inattentional blindness” [58], [59] can occur even when a stimulus is salient in terms of its colour or movement, thus posing a challenge for the design of safety-critical emergency alerts. The likelihood of inattentional blindness is increased with the attentional

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demands of the task [60], working memory load [61], the need to maintain information in visuo-spatial memory, low expectancy of events [26] and during periods of high tempo activity with competing visual demands [62]. An object is more likely to be detected if it is near the focus of visuo-spatial attention [59], but proximity is not sufficient for detection and it can still be missed [58]. In demanding tasks, operators may experience attentional narrowing or 'tunnelling' [63] and become fixated on a particular facet of their task, to the exclusion of other equally – or perhaps more – important aspects of the environment [64].

Neuroimaging studies related to attention have revealed three networks related to different aspects of attention: alerting, orienting, and executive control [65].

- Alerting is defined as maintaining a state of high sensitivity to incoming stimuli, and is associated with the frontal and parietal regions of the right hemisphere [66].
- Orienting is the selection of information from sensory input, and it is associated with posterior brain areas including the superior parietal lobe (related to the lateral intraparietal area in monkeys), the temporal parietal junction and the frontal eye fields [67].
- Executive control is defined as involving the mechanisms for resolving conflict among possible responses. It activates the anterior cingulate and the lateral prefrontal cortex [68]. This attention network affects visual processing, which is one of the most efficient ways to enhance the stimulus representation for the purpose of selection.

Shift in attention need not entail an overt shift of the eyes. Nevertheless, spatial attention and the eyes often move about the environment in "tandem". For example, an abrupt onset in the visual periphery can reflexively "capture" both attention and the eyes [69], [70]. In this way, attention can be allocated in overt or covert modality: **overt**, when an observer moves his/her eyes to a relevant location and the focus of attention coincides with the movement of the eyes, or **covert** [71], when attention is deployed to relevant locations without accompanying eye movements. The deployment of covert attention aids us in monitoring the environment and can inform subsequent eye movements. Humans deploy covert attention routinely in many everyday situations, such as searching for objects, driving, crossing the street, playing sports and dancing. Covert attention allows us to monitor the environment and guides our eye movements (overt attention) to locations of the visual field where salient and/or relevant information is. Moreover, covert attention plays an important role in social situations, for example, in competitive situations (such as sports activities). Moving the eyes also provides a cue to intentions that the individual wishes to conceal, a predicament solved by covert attention.

Spatial resolution, our ability to discriminate fine patterns, is not uniform across locations in the visual field. It decreases with eccentricity. Correspondingly, signals from the central parts of the visual field are processed with greater accuracy and faster reaction times [72].

Lack of attention/vigilance or distraction usually affects human performance by causing the omission of procedural steps, forgetfulness to complete tasks, and taking shortcuts that may not be for the better. A performance decrement can be noticed when attention/vigilance, workload and task difficulty increase; the reaction time and number of errors increase as well, while accuracy and number of completed tasks decrease. Reduction of the performance in monitoring, tracking, auditory discrimination, and reduction of visual field can be observed too.

5.3.3. Mental workload

Mental workload is a hypothetical construct that describes the extent to which the cognitive resources required to perform a task have been actively engaged by the operator.

The term is used to describe aspects of the interaction between an operator and an assigned task. Tasks are specified in terms of their structural properties; a set of stimuli and responses are specified with a set of rules that map responses to stimuli. On the other side, there are expectations regarding the quality of the performance, which derive from knowledge of the relation between the structure of the task and the nature of human capacities and skills. Workload is invoked to account for those aspects of the interaction between a person and a task that cause task demands to exceed the person's capacity to deliver. Mental workload is clearly an attribute of the information processing and control systems that mediate between stimuli, rules and responses.

Increase of workload and task difficulty lead to a performance decrement that reflects in a decrease of accuracy and number of completed task, while reaction times and number of errors increase.

The increase of mental workload could lead to a Situation Awareness decrease which, in turn, could lead to worse performances. However, the adoption of compensation strategy can result in the lack of visible effects of workload variations on subject performance.

5.3.4. Cognitive control

The efficiency of humans in coping with complex situations is largely due to the availability of a large repertoire of different mental representations of the environment from which rules to control behaviour can be generated *ad-hoc*. Nowadays, several models defining the different types of cognitive human behaviour are available [73] such as the *Skill, Rule and Knowledge* (SRK) model, proposed by Rasmussen in 1983 [74]. Accordingly with basic different ways of representing the constraints in the cognitive human behaviour, three typical levels emerge: skill-, rule-, and knowledge-based level [75].

At the skill-based level, the types of activity are usually routine and automated, such as annotating flight strips for air traffic controllers. For the pilot, it can be seen as the aircraft handling which is clearly linked to the level of flight training. This type of behaviour tends to encourage errors which are associated with attentional or memory failures.

At the rule-based level of activity, an individual uses certain types of response to known and often rehearsed scenarios. For instance, in the ATC environment, standard operating procedures would be classed as rule-based behaviour. The use of separation procedures and weather limits would also be classed as a similar type of activity. The pilot working method is oriented to Rule-based behaviour even in emergency situations thanks to do-lists, check-lists and Crew Ressource Management (CRM). Rule-based mistakes involve the application of already known but inappropriate solutions to problems that have been encountered many times before or which have been highly trained. Rule based mistakes can be divided into two types: the misapplication of good rules and the application of bad rules.

Knowledge-based behaviour is the result of skill, ability, observation, training and experience. These variables enable the individual to tackle novel, difficult or even dangerous situations with adequate reliability and in most cases the likelihood of a successful outcome. Knowledge-based mistakes occur when a person is attempting to solve a novel problem, namely searching for a solution to a problem which has not been previously encountered in training or experience. The main problems with this situation are that the individual is forced into a position of active reasoning and retrieval from long-term memory, which has an influence on the working (mid-term) memory capacity. Non-standard emergencies where no procedures or checklists exists may induce a Knowledge based behaviour.

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Nevertheless, to cope with those situations, pilots have to use a method like FORDEC. FORDEC is the model used by the EU/EASA/JAR NOTECHS (non-technical skills) as Behaviour Marker for CRM Skills. It is being use by a lot of companies worldwide to handle non-standard emergencies.

FORDEC is an acronym and stands for:

- F – Facts (what is the problem)
- O– Options (hold, divert, immediate landing etc.)
- R – Risks/(Benefits sometimes included) (what is the downside of each option, what is the upside, i.e. a runway may be further away but is longer)
- D – Decide (which option)
- E – Execute (carry out selected option)
- C – Check (did everything work/go to plan, what else needs to be done)

Table 2 provides an overview of the levels of cognitive control.

	Mainly conscious type of control	Conscious & Automatic type of control	Mainly automatic type of control
Routine- expected situation			SKILL-BASED
Familiar or trained-for problems		RULE-BASED	
Novel, difficult or dangerous situations	KNOWLEDGE-BASED		

Table 2. Levels of cognitive control

5.4. Human Performance

Pilots' performance is recognised to be impacted by all the aforementioned factors, namely, stress, emotions, attentional resources available, attention focus and so on. In the recent years the concept of **Human Performance Envelope (HPE)** [76] has been introduced as new paradigm in Human Factors. Rather than focusing on one or two individual factors (e.g. fatigue, situation awareness, etc.), it considers their full range, mapping how they work alone or in combination to lead to a performance decrement that could affect safety.

5.4.1. Automation impact on Human Performance

The HP envelope currently being considered by the [Future Sky Safety project](#) is a first good approximation of what may be expected: a prominence of workload and stress, then attention, communication, vigilance, and fatigue (see Figure 10).

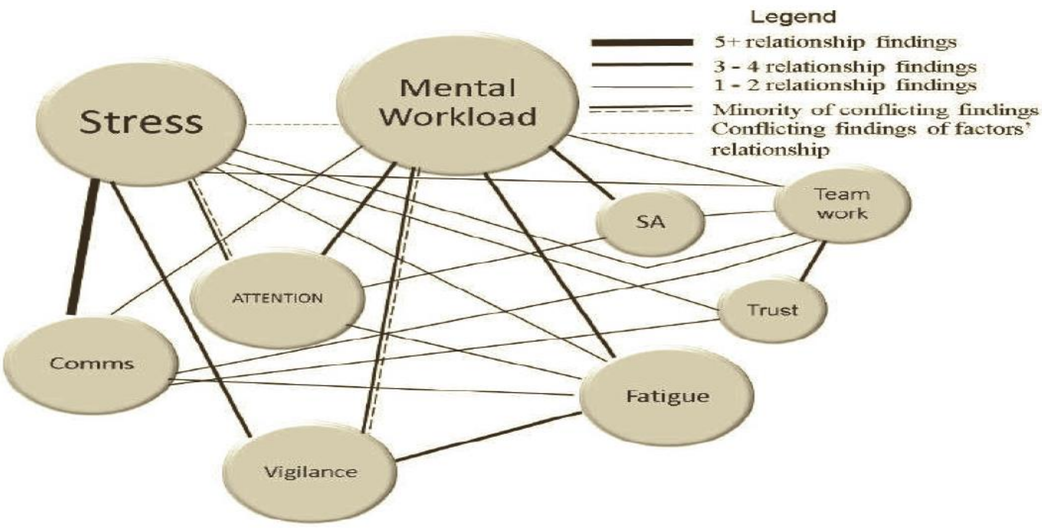

Figure 10: The HP envelope being considered by the Future Sky Safety project for pilots

It is reasonable to expect that the future pilot HP envelope will be different than the one we would use today. It will have different underlying HF concepts, or at least a different weight among them. For instance, pilots are expected to move to a monitoring position of highly automated systems, with very few tactical interventions, strategic planning by exception (only when automation cannot find a solution), need to intervene rapidly to recover disruptions or unexpected events.

Workload may be even less primary, but with sudden bursts when recovery actions are needed. Stress will be indeed a major factor, both in normal conditions (when pilots will need to rely on automation without having the possibility of controlling it) and in disruptions. Such a monitoring role will probably require even more attention that pilots today.

A full understanding of the future HP envelope and of the underlying HF factors will allow the optimization of Human Performance, by identifying human bottlenecks and limitations. This concept is aligned with the ACARE Strategic Research Agenda [77].

This concept applies to nominal conditions, when the HP envelope analysis would determine the human bottlenecks to higher automation levels, e.g. lack of trust, too high stress level, or lack of adequate attentional patterns. But it is also relevant in degraded conditions, where it will be possible to track the temporal variations of the HP envelope. As a practical example, this could mean forecasting what would typically happen to the stress and workload levels in case of automation disruptions and when their levels could be considered "back to normal".

In the framework of the already mentioned SESAR 16.05.01 project, a method to identify design principles linking the level of automation with HP issues, has been generated (see an excerpt of it in Table 3). It has to be noted that the results of this investigation are highly related to the knowledge on HFs currently available, and to experiments conducted with currently available automated tools.

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Table 3. Example of design principles and HP impact of different automation levels

Cognitive Functions	Automation support example (current):	Example of design principle for selecting a specific automation level	Impact on HP
Information Acquisition (IAC) Acquisition and registration of multiple sources of information. Initial pre-processing of data prior to full perception and selective attention.	• *Visualization of traffic on CWP through Multi-Radar Tracking System.* • *Advanced - Surface Movements Guidance and Control system (A-SMGCS) airport moving map*	***IAC-1.1: Level <u>A2</u>*** These functions transmit information on the process to be followed **without any filtering, highlighting and integration** of the available data. These functions should be preferred when the two following conditions are met: -the concerned activity requires the processing of a **limited number of information items** by the human operator **-the information can be accessed through a** limited number of information sources**.**	• Increase task demand and cognitive workload • Simultaneous tasks competing for user attention or causing interruptions of high workload activities, reducing efficiency and increasing the risk of human error • Excessive 'head down' time, with potential negative impact on human performance • Reduce accessibility to relevant information, with negative impact on decision making processes and situation awareness.
Information Analysis (IAN) Conscious perception, manipulation of information in working memory. Cognitive operations including rehearsal, integration, inference.	• *STCA-Minimum Safe Altitude Warning (MSAW)-Approach Path Monitor (APM)-Area Proximity Warning (APW) visual and aural alerts* • *A-SMGCS route-planning function* • *MTCD conflict*	***IAN-1.2: Levels <u>B4-B5</u>*** These functions **perform systematic information analysis and trigger automatic alerts as appropriate**. These functions should be preferred when the two following conditions are met: - for operational reasons the user should be informed as soon as possible **of critical results of the information analysis** - the internal logic of the automated function has the **capability to process the most relevant operational constraints and/or dynamic elements** of the concerned operational environment with an impact on	• Induce workarounds and higher workload in human operators. • Induce misuse, disuse or abuse of automation • Distrust in automation and increase workload

	alerting function • *Monitoring Aids (MONA) alerts* • *A-SMGCS alerts*	the performance of the function, thus reducing the risk of triggering nuisance alerts to an effective minimum.	
Decision and Action Selection (DAS) Selection among decision alternatives, based on previous information analysis. Deciding on a particular ('optimal') option or strategy.	• *AMAN visualization of proposed sequence of aircraft* • *AMAN speed advisories*	***DAS-1.3: Levels <u>C5-C6</u>*** These functions do not inform the human of the selected option or inform her/him only on request. These functions should be preferred when it is possible to safely and efficiently isolate a limited set of parameters and variables to be managed autonomously by the automation. In such cases the best way of generating decisions is delegating them to the automated function, leaving to the human operator only the possibility to interrupt the following action implementation.	• Increase task demand and cognitive workload • Increase task load and reduced acceptance.
Action Implementation Support Functions (AIS) Implementation of a response or action consistent with the decision previously made. Carrying out the chosen option.	• *Automatic Flight Plan Correlation function* • *Automatic Special Service Request (SSR) code assignment function*	***AIS-1.1: Levels <u>D2-D3-D4</u>*** This level, which perform action implementation only after human initiation, should be preferred when it is not possible to safely and efficiently isolate a limited set of parameters and variables to be managed autonomously by the automation. In such cases the best strategy for action implementation is based on a cooperation between the human operator and the automated function, maintaining the human fully in control of the situation.	• Reduced vigilance and loss of situation awareness • Loss of skills and proficiency • Impact recovery from system failure • Reduce situation awareness. • Induce workarounds and higher workload in human operators. • Reduce the human potential to adapt to normal and abnormal situations

A brand-new contribution will be the study of the transitions among levels, providing information about the impact of transition on HP and generating guidelines to cope with them minimizing system performances degradation.

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5.4.2. The Human Performance Envelope

From a theoretical point of view, the idea behind the HPE is that specific combination of different levels of relevant cognitive aspects will positively or negatively impact human performance. Figure 11 provides some simple (fictional) examples: high levels of attention and vigilance, low levels of stress and workload and a mainly skilled type of behavior will produce a good level of performance (green) while opposite values will decrease the level of performance (red), pushing the operator out of his/her "envelope".

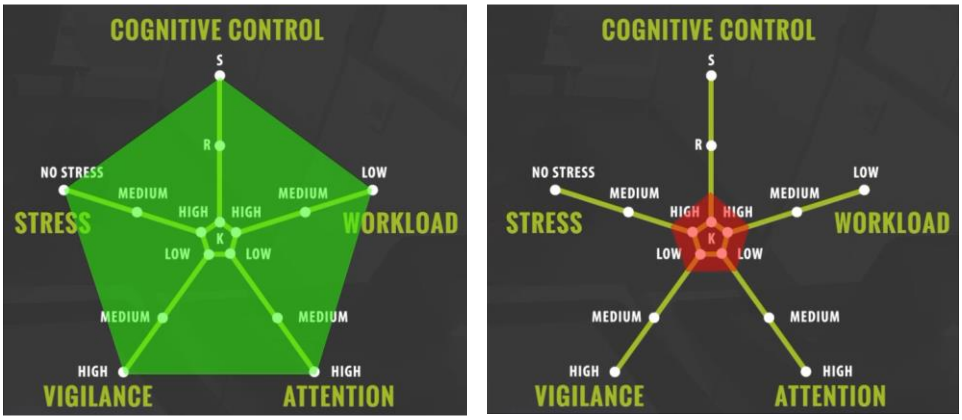

Figure 11: Examples of the Human Performance Envelope concept

During the project, we will consider the impact of the proposed solutions on the relevant human factors identified in the previous paragraphs. In doing this, we will consider only the impact on single factors but on many of them and on the mutual impact they have on each other.

6. Machine Learning (ML) and Cognitive Computing (CC) algorithms

6.1. Introduction

Human beings have always tried to understand what makes them think, in order to recreate this ability in intelligent machines. A first example comes from ancient Greece by the hand of Aristoteles, whose work was based on explaining the rational functioning of the mind [78]. Ramon Llull proposed the idea that reasoning could be captured in a machine in an artificial way, introducing the concept of logical machines [79], capable of creating knowledge by combining undeniable truths through simple logical operations. Additionally, Hobbes promulgated that reasoning was nothing more than calculations [80]. These examples and many others propitiate the birth of artificial intelligence (AI) dates from remote origins. From these origins to the present, psychologists, engineers and mathematicians have contributed to the AI development.

In the 1950s, Alan Turing published the article "Computing Machinery and Intelligence", in which he went into the idea that a machine can imitate how the human mind works [81]. In addition, he proposed a mechanism capable of determining whether a machine is intelligent, known as the "Turing test". Just a year later, Marvin Minsky was inspired by the model proposed by Nicolas Rashevsky in 1930 to give rise to the first digital neural network [82]. However, the term artificial intelligence did not exist as such until 1956 after its assignment at the Dartmounth congress, organized by different researchers interested in developing machines that imitate human behaviour. At that conference, Professor John McCarthy of Stanford University named artificial intelligence, which he defined as "the science and ingenuity of making intelligent machines, especially intelligent computer programs". During the meeting, which lasted two months, future lines of action in this field were defined, starting from the hypothesis that "any aspect of learning or any other characteristic of intelligence can be defined so precisely that a machine can be built to simulate it" [83].

During the following years, the high expectation about this field led to a bad time for artificial intelligence in the 1970s and 1980s, with three major setbacks [84]. In 1973, the first of these took place after an investigation into the concept of the automaton, the central nervous system and robots. James Lighthill wrote an article about this research [84] concluding that no progress was being made in artificial intelligence; all this accompanied by the suspension of funding for research on intelligent systems. Later, in 1982, a computer was designed in Japan that would be capable of deducing and processing knowledge, in which up to 850 million dollars were invested, but after ten years no progress was made, giving rise to the second setback [84]. Finally, in 1984, the third setback occurred. In this case, Stanford University began to create Cyc, an encyclopaedia that encompassed all human knowledge. In the late 1990s, however, it was overtaken by Internet search engines [84].

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A key conclusion was drawn from these failed experiments. Prior to the creation of intelligent computers, it was necessary to know how to provide them with the required information. The main problem was that although some knowledge was innate, most was learned from the experience, so that they cannot be supplied entirely by the human being, so machines had to learn themselves from the environment, either with databases or search engines.

Since 1990 the term "Cognitive Systems" has been used, which mainly aims to speak of AI not simply as the development of artificial systems but as the ability to teach computers to think like human beings, much more quickly, providing these systems with technology that models the biology of the human brain. This era is known as “congenital or cognitive computing” and it is characterized by the combination of the most advanced computing with nanotechnology and neuroscience, achieving computers with knowledge, capable of learning from past experiences, extracting hypotheses and offering answers [85].

Capturing information from the environment is of extreme importance for artificial intelligence. Nowadays, a huge amount of data is being daily generated and changing continuously, making Big Data technique essential in the 21st century [86], [87]. An example of how big data has been introduced into intelligent systems is clearly illustrated in IBM's Watson computer [88]. This computer stored around 200 million pages of data in its memory, consuming a capacity of four terabytes of storage, which allowed this device to defeat in February 2011 the strongest opponents of the American television program Jeopardy's, in an open-domain answering match. Watson was not revolutionary in AI because the amount of data he stored, but due to its ability to read clues in natural language. Watson was able to extract the main idea of the clues precisely, and then search for the answer among his internal information sources. With the help of Machine Learning, the answer with the largest confidence level was selected as the definitive solution.

Another revolutionary system, known as AlphaGo, was created by DeepMind. This machine, thanks to the use of Deep Learning taught itself to play Go, making hundreds of games and learning in each of them [89]. AlphaGo was able to evaluate positions and select movements, becoming the first machine capable of defeating Lee Se-Dol (the world champion in Go) in 2016. This event caused an important revolution in the media, as AlphaGo carried out a special game mode, superior to the human ability to calculate probabilities of defeating his opponent. Today, DeepMind is working on a similar project oriented to the Starcraft game [90], [91].

The aforementioned projects are just some pieces of evidence of how the social demand for intelligent systems has grown considerably in recent years. Many areas of daily life, such as the automotive, industrial, medical, aeronautical and financial sectors among others demand digital assistants which allow reducing costs. This social demand has forced the creation of what is known as artificial intelligence 2.0. In this sense, two main goals are proposed, which are to achieve hybrid intelligent systems combining machines and humans, and to create more complex intelligent systems, commonly known as "man-in-the-loop" [84]. During the next sections and in-depth analysis about the impact of artificial intelligence 2.0 on economy in general and several sectors of activity in particular is carried out.

6.2. Impact of AI and CC on companies and worldwide economy

With the arrival of the industrial revolution at the end of the 18th century, there was a great change in employment. On the one hand, jobs increased in the industrial sector and to lesser extent services, to the detriment of the agricultural sector, due to the incorporation of machinery in factories and agricultural work. With the incorporation of this machinery, it was possible to complement and extend the manual work developed by people, replacing some jobs but, at the same time, improving productivity and adjusting the products of the companies to the needs of the consumer [92].

Later, with the digital revolution in the mid-twentieth century, this trend was intensified with the advent of the Internet and computers, increasing employment in the service sector and decreasing the manufacturing industry and the agricultural sector. In this case, it was computers that complemented people's daily activities. By automating processes, it was possible to replace repetitive mental tasks carried out by workers, resulting in a change in the employee's profile [93], [94].

An analogy between these two revolutions and the one that artificial intelligence is expected to generate can be established. On the one hand, given the high potential of this technology, intelligent systems are expected to be capable of imitating the human mind, so it will be possible to replace various routine and repetitive tasks of the employee by these machines. On the other hand, the working speed of this technology is higher than the speed of human thought, so it will encourage to perform tasks more efficiently, thus achieving an increase in productivity. At first, this might appear to be the replacement of the human being by machines when it comes to working, however, what is really expected is a change in the profile of the worker. Greater qualification of the worker in more technical aspects (i.e. engineers, specialized technicians and data analysts) and greater competences will be of vital importance to use artificial intelligence tools, which require greater digital and technical knowledge [94].

The fact of incorporating artificial intelligence into the activity of companies is going to open a gap between them [94]. Thus, it will be possible to compare those known as early-adopters and the most lagging. Late-adopters would tend to lag behind their closest competitors since the impact they will generate will be less since AI opportunities will have been previously captured by front-runners, and they lag behind when it comes to developing capabilities and attracting talent. In addition, companies that do not adapt to new developments will see their market share reduced, along with a worsening of the associated costs and an increase in delivery times compared to the competition [95].

Artificial intelligence is going to generate a great impact on the world economy, and it is going to be possible to perceive notorious inequalities between countries that incorporate these technologies in their activities and those that do not. Initially, the differences will be smaller because in the early stages it will be necessarily make a great economic effort associated with the costs of research and technological development, so the benefits will take time to be perceived in the economy of the countries. Later, there will be an accelerated increase in the benefits in those countries that receive this innovation at an early stage, opening the gap between countries even more. In addition, gains will be accelerated not only by technological advancement and consumption of AI, but also by increased data and exchange of information and knowledge with consumers, which will help to better understand their behaviour, preferences and needs [96].

The greatest economic impact associated with AI will be experimented by the United States and China, although the evolution will be different. These two countries together are responsible for much of the evolution of AI, very distant from the rest in terms of publications and patents. Although China

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currently has a great potential in innovation and development, as can be seen in applications such as Baidu, Alibaba, or the fact that it won the ImageNet competition, it is a less technologically developed country so the impact of AI will have an effect later than in the USA. For its part, the U.S. currently presents the largest source of technology in the world, which is used to innovate and make their activity more productive, although there are great differences between sectors. One step below, a broad spectrum of countries, such as Germany, France, Sweden, Japan and Canada will have the capacity to drive AI on a large scale even though productivity growth has been slower. A third group is made up of countries that currently have weaker starting conditions than the aforementioned two groups so that the expectation of benefits from AI are more moderate. This group is made up of countries such as India and Italy. Finally, the last group composed of the underdeveloped countries, which don't have enough technological and digital resources to integrate AI into their economy due to its situation of poverty [95], [97].

6.3. AI applications in different sectors

After a brief review of the evolution of the industry and an explanation of the impact that AI may have on the world, this section proceeds to present this same information among different existing sources of the economy. It describes the main sectors where AI has had special relevance such as the financial, retail, health, education, automotive and aerospace. Specifically, the most important milestones within each of them are highlighted, as well as the future line of action since it is a technology in growth.

6.3.1. Financial

In recent years, the presence of artificial intelligence has increased in the financial sector. This is due to the large amount of data generated on a daily basis and the greater calculation capacity of the systems [98]. In this sense, artificial intelligence techniques in this sector can provide greater benefits in companies where managers and directors use these techniques to gain a competitive advantage in the market.

The first great advance of artificial intelligence in the financial sector was to create a system of digit recognition, which made it possible to speed up financial work since, for example, machines can read bank records autonomously, thus freeing the employee from this activity [99].

In addition, artificial intelligence has led to the creation of applications with more advanced functions. Currently, Chatbots, especially used by the "millenials", are generating a great impact within the financial sector [100]. A clear example of this is Charlie, from Propel or Plum, from Facebook. These applications are in contact with users' bank accounts and allow them to easily know their income and expenditure status. In addition, artificial intelligence makes it possible to create personalized savings plans and provide information to users based on data provided by them [101].

An example of this would be the project carried out by Google Cloud and Data&Analytics of BBVA, who with recurrent neuronal networks have developed a model that, knowing the habitual income and expenses of customers, as well as their origin and destination, provides them with an estimate of their future income and expenses, so that they can plan their actions [101].

Other applications of AI within the financial sector can be the detection of fraud and money laundering and the automation of processes, as well as automatic payment after facial recognition of the customer, the latter thanks to the use of people identification and image processing [102].

On the other hand, in addition to the benefits that AI can bring to financial institutions and the user, it can generate a great social impact since techniques are being developed and favour financial inclusion in vulnerable populations. Fintech companies propose alternative credit solutions for populations with difficult access to banks [95].

6.3.2. Retail

Within the changing retail environment, it is the needs of consumers that drive their purchasing decisions. The main objective will be to know or estimate the evolution of these decisions in the future, in order to know the evolution of the sector [103].

In retail, there are many possibilities to introduce artificial intelligence. Currently, this technology is used for stock control and to conduct market research, specifically consumer preferences and thus facilitate companies to know and anticipate consumer demand, allowing them to design products according to their preferences. The incorporation of AI in companies can be relevant, in the way that it allows to obtain a competitive advantage regarding to the rest of companies dedicated to the same activity [96].

In addition, AI also helps the consumers' buying speed, because knowing their preferences can help them find the product that best suits their desires and needs more quickly, as is the case with online shopping recommendations [104].

A revolutionary application in this field is Amazon's design of its Amazon Go supermarket. In it, the customer makes the purchase freely without going through the checkout. The payment mechanism will be made automatically when leaving the establishment, leaving the amount of the purchase registered thanks to sensors and cameras located on the local [105].

6.3.3. Healthcare

In the clinical context, artificial intelligence can be used as a method to support professionals and to minimize diagnostic and therapeutic errors that are unavoidable in human practice [88]. In this field, the inclusion of artificial intelligence is really relevant, as increasing the quality of patient care depends directly on the speed of detection and the accuracy of diagnoses. Thus, intelligent systems make it possible to determine patient diagnoses or even detect pandemics and prevent their expansion [106]. For this, it is necessary that cognitive systems know the medical condition of patients, as well as their symptoms and other information that may be useful for the diagnosis such as family history, previous similar cases to the patient's, their demographic condition, age and more, to complete the EMR of each situation [107]. With all these data, the intelligent system analyses possible diagnoses, giving each of them a probability of occurrence, finally accepting the most likely hypothesis.

The IA has its great application in the diagnosis by images [108] reason why it requires the use of deep learning and the use of CNN, as well as NLP when the data are not structured [107]. Some examples are laboratory reports, physical examinations and guidance notes, as natural language processing techniques can extract information from the text that may be relevant for diagnosis.

As an example, for the detection of skin cancer, there are applications for Smartphones that, using image recognition (image classification and object detection) can determine the existence of a tumour after taking a photograph of a mole [109]. These applications are far-reaching and can be a social asset as people in remote locations with difficult access to medical care can quickly obtain a diagnosis .

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Another example would be the creation of portable devices that offer early detection of diabetes thanks to integrated sensors that measure the heart rate of the carrier [110].

6.3.4. Education

The application of artificial intelligence in the education sector (also known as AIED) has been a subject of study for decades [111]. One of the main objectives is to provide a deeper understanding of how learning takes place and the influence on it of other factors, such as the socio-economic and physical context of the person.
Intelligent tutor systems have a series of knowledge, both of the contents and of the students, as well as learning methodologies that allow them to help the student, which guides them throughout the learning process and problem solving. Intelligent Tutoring Systems (ITS) use AI techniques to simulate individualized tutoring, offering the activities that best suit each learner's needs and providing feedback [112]. Some ITS seek to motivate students to take control of their own learning, thus hoping to develop their responsibility and maturity. Today's ITS use machine learning techniques, self-learning algorithms and neural networks to make appropriate decisions about what content provide to the learner [113].
Another alternative to these intelligent tutors is the automatic test evaluation systems [114], which in addition to correcting the student, allows him to know his strengths and weaknesses. Among the alternatives of this learning model are ToL, based on the online test [115], and CELLA, for the study of the English language [114].
Furthermore, there are other systems that allow learning, not in terms of subject matter, but in terms of aptitudes. This is the case of collaborative learning, which teaches and guides students to develop their group work skills and improve interaction between them, as could be done with DEGREE [116].
Another more dynamic form of learning is learning based on games [114]. With it, students are motivated to develop skills and knowledge, and even make students aware of issues related to society and citizenship, as is the case of NetAid's learning method, which aims to raise awareness about poverty [117].
In addition, part of these systems can be used both inside the classroom and outside it through the Internet, thus allowing continued education at any time and place.
Another technique implemented to support learning is the use of virtual reality, which can provide immersion experiences that simulate certain aspects of everyday life. This function added to artificial intelligence, allows the user to interact and make decisions in situations that could be real, taking records of different behaviours. Within these experiences, they can assume different roles. For example, FearNot is a virtual reality system designed for schools that present environments related to bullying. It seeks to help people who have suffered it by giving advice on behaviours to adopt in different situations [118].
The AIEd used in classrooms has evolved, and at present the design and implementation of intelligent classrooms or "Smart classrooms" is being pursued. It is possible to combine cognitive systems with data mining techniques to track students' behaviour and their level of attention and concentration in class, for example, by collecting attendance data and submitting papers to identify and support students at risk of dropping out of school [119]. Other researchers are working on new interfaces, such as natural language processing, speech, gesture recognition and eye-tracking, among others, that could be applied to the field of education.

6.3.5. Automotive

The automotive industry is one of the quicker to embrace change in technology [120]. The application of artificial intelligence in this area brings great benefits to society, especially in relation to a very important issue such as road safety and protection [121].

AI is also present in the automotive sector offering help to drivers. The automotive sector pursues the design and creation of cars that act proactively in the assistance to the driver, and even some cars are capable of driving completely autonomously.

Autonomous cars need to have a large amount of data in very short periods of time to continuously pay attention to all possible scenarios (pedestrian crossings, signs, cyclists...) that may arise and to respond quickly and safely [85]. For that reason, cognitive cars have integrated GPS systems, cameras and sensors that allow them to capture all the information of the environment and other utilities such as obstacle detection and visual navigation [122]. Since the variations of the environment are very fast, it is necessary that the car has cognitive capacities, in other words, that it is capable of learning and making decisions from its own.

Some tasks that intelligent cars are able to do is the detection of road hazards, introduced by General Motor in 2012 [123], or the automatic parking developed by several companies. To carry out this action, the car must be able to locate and delimit the parking area and, making use of sensors and cameras, perform the necessary manoeuvres to leave the car parked [124].

Another example of the application of AI in that sector is the idea of Nissan about developing a neuro car, which allows monitoring the driver's vital signs, such as skin temperature and brain activity, which can be relevant when detecting situations of stress at the steering wheel [85].

It is also important in this sector to pay attention to the advent of 5G networks and to the Internet of things. These networks, combined with the integration of AI and cloud computing, are going to bring about a major change in the paradigm of driving vehicles in the coming years, referred to as the cognitive internet of vehicles (CIoV). It is expected that the combination of all this technological environment will produce an improvement in transport safety based on the information gathered from the network and the physical space. In [125], some of the innovations that the creation of the 5G will produce in this sector are presented.

6.3.6. Aerospace

Air Traffic Management benefits for a long time of complex optimization techniques [126] that are strongly linked to Artificial Intelligence. Maybe the most well-known problem is the departure slot allocation as it impacts any passengers in any aircraft in Europe. The Network Manager Operation Center (NMOC, previously known as Central Flow Management Unit) plans European departures to avoid overloading “en-route” sectors. Barnier, [127], used constraint programming to study the slot allocation to respect sector capacities while Allignol [128] a decade after, considering that aircraft could follow a four-dimensional trajectory, proposed departure slots with conflict free trajectory using evolutionary algorithm [129].

The route network was initially created with radio-navigations beacons on the ground, heading towards or away from a beacon. The availability of positioning systems enabled new route deigns. The objective is to minimize trajectory lengths of major aircraft flows and reduce as much as possible small

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flows, bundling techniques [130] produce graphic results while Mehadhebi [131] studied the edge and node positioning problem. Airspace sectorization brings additional constraints; a crossing point must be far away from the sector entrance to allow controller action. Adapted Voronoï diagram help to design airspace, taking into account those constraints and in addition to avoid overloading sectors. Riviere [132] applied simulated annealing algorithm to a specific route network “Sector-less”. Some other studies regard 3d-tubes instead of 2d-routes, which is a significantly bigger problem, Gianazza in [133] used a hybrid evolutionary algorithm with an A star algorithm embedded inside the mutation operator. Even if the airspace design is defined, according to traffic and controller’s capacity, sectors can be grouped and ungrouped. Gianazza, in [134] used neural network to select complexity metrics to predict controller workload and eventually predict airspace partitioning.

Airports are considered as a bottleneck for air traffic. Some mechanisms, such as arrival and departure management (AMAN, DMAN), improve coordination with approach sectors and minimize taxi times, reducing the risk of congestions. Another problem is gate assignment and reassignment (in case of unexpected events). Among others, constraints to consider could be aircraft waiting time, passenger comfort (distance to luggage or connection). The authors of [135] compare different crossover techniques for genetic algorithm to solve the problem. Regarding environment, new technologies such as TaxiBot could reduce fuel consumption for taxiing, aircraft starting engine closest to the runway. Lancelot in [136] studied a system integrating autonomous vehicles with a multi-agent system approach. Gottelland in [137] simulated Charles De Gaulle airport using genetic algorithms to minimize taxiing time, ensuring minima separation between aircraft and at the same time respecting runway capabilities.

Air traffic controllers could also greatly benefit of Artificial Intelligence to support them to make decisions, from conflict detection to conflict resolution. Conflict detection problem depends mainly on trajectory prediction whereas conflict resolution depends on conflict detection, aircraft capabilities, controller and pilot acceptance. Durand in [138] trained a neural network with a genetic algorithm to solve conflicts between two aircraft. The same genetic algorithm was used in [139] to solve every conflict over the French airspace on a loaded day with a centralized approach. A distributed approach was also studied in [140] by using an A* algorithm, solving independent conflict in parallel, and dependant conflict sequentially. In [141] an Ant Colony Optimization was used to solve aircraft conflict and dealt with large problems but not real ones.

Artificial intelligence and cognitive computing inside cockpit are a relatively new research area. A few years ago, Airbus understood that cognitive computing has a role in the future of aviation. Aircraft manufacturers are used to record data, such as in the aircraft black box or flight recorder. But with cognitive computing, more data has to be recorded and stored to feed algorithms. Ronny Fehling in [142] acknowledged that "airbus embarked two year ago on a Big Data journey". The data storing methods will not be reviewed here as it is a research area by itself and not in the project objectives. However, such as any deep-learning method, cognitive computing requires data to learn and improve its behaviour. Airbus and IBM developed a cognitive approach for maintenance and with the analysis of aircraft sensors, current maintenance, flight operations and other data, they propose a cognitive aircraft health advisor. Both Airbus and IBM applied this research. After one year of collaboration with Airbus, Delta Air Lines has become the first costumer of the Prognostics and Risk Management solution. IBM implement the assistant with Korean Air fleet with its own defect database.

6.4. Review on ML and CC algorithms to solve AI tasks

In this section, we expose a description of the predominant tasks of artificial intelligence, object of study during the last years. The evolution of these techniques is directly related to the applications they are intended to be useful, whether they belong to a specific sector of the economy or to a particular social good. A large number of the techniques that have been present up to now in AI are applied to issues such as improving the reconciliation of equality and the inclusion of the most disadvantaged people in society, as well as in education, security and justice and health and hunger [143]. Figure 12 shows the applicability of each of the artificial intelligence techniques to the different social goods, in a graphical way.

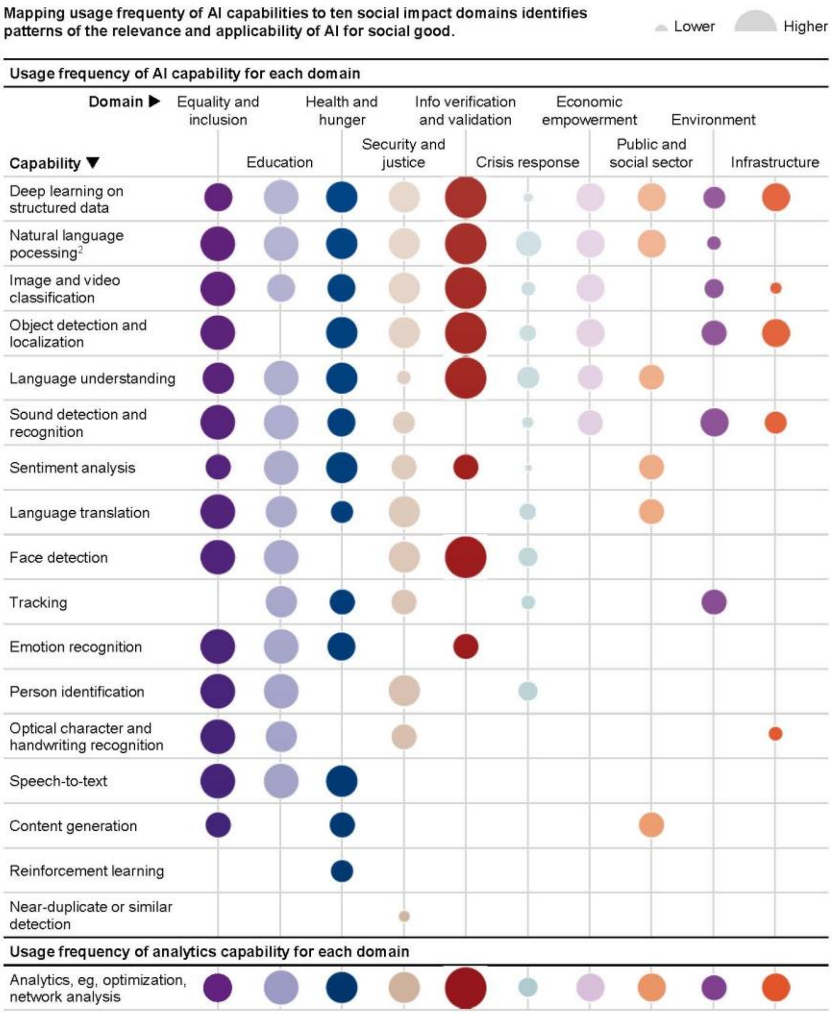

Figure 12. Graphical view of AI tasks in different domains. Adaptation of McKinskey Global Institute notes [143].

As can be observed in the previous figure, natural language processing, image and video classification, object detection and deep learning applied to structured data are the tasks with more incidence in society. On the contrary, content generation and reinforcement learning are relatively new techniques with less incidence but with promising future. In the following sections, we review the current state of the most incident and promising techniques to solve artificial-intelligence tasks.

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6.4.1. Image classification

Probably the most well-known task in the computer vision field. Image classification consists on automatically assigning a label class to a given input image. Before the explosion of deep learning, the efforts of the scientific community focused on discovering novel and effective image descriptors able of converting the relevant information contained in the image into a feature vector. After this step this encoded information was used to train a classifier in charge of identifying the objective classes. Local binary patterns (LBP) [144], histogram of oriented gradients (HOG) [145], scale-invariant feature transform (SIFT) [146], Speeded-up robust features (SURF) [147] and gabor filters [148] are only some examples of the most representative image descriptors proposed in the literature. In the same way, support vector machines (SVM) [149], random forests [150] and feed-fordward neural networks [151] were one of the classification algorithms with more incidence in the computer vision community to solve image classification tasks.

With the arrival of convolutional neural networks (CNNs), the hand-crafted feature extraction moved to an automatic feature extraction by learning automatic filters. The pioneer work of Krizhevsky et al. [152] introduced a CNN (AlexNet) to solve the annual ImageNet Large Scale Visual Recognition Challenge 2012 (ILSVRC-2012). Their model achieved an error rate of 16.4% and the network consisted of eight layers with weights including five convolutional layers and three fully connected layers with a final 1000-way softmax, and three max pooling layers. After this contribution, each year in ILSVRC, novel CNN architectures were proposed with the aim of decreasing the classification error rate. In 2014, Simonyan and Zisserman [153] analysed AlexNet architecture and made some modifications to improve the classification performance. Simonyan and Zisserman proposed receptive fields in the first layers of 3x3 with stride 1, much smaller than those used by their predecessors (11x11). At ILSVRC-2014 they presented VGG16 and VGG19 and obtained first and second place in the localization and classification tasks. In ILSVRC-2015, Microsoft Research Team of Asia (MSRA) designed the Microsoft ResNet architecture based on the concept of residual learning block, which allowed them to beat records of detection, localization and classification. To overcome the problem of degradation in deep knowledge networks, He et al. [154] proposed residual mapping. Using shortcut connections, they obtained five residual networks whose convolutional layers are 3x3 with stride 2. Compared to VGG, ResNets are less complex and use fewer filters. One year later, François Chollet (author of Keras framework) proposed the Xception architecture [155], based on the idea that spatial correlations and correlations between channels are disconnected, so they can be mapped separately. Thus, it is an extension of Inception architecture (proposed at ILSVRC-2014 by Szegedy et al. [156]), replacing its modules with depthwise separable convolutions. From this, Chollet incorporated an independent convolution on each input channel and then a pointwise convolution, which projects the output of the channels onto a new channel space. In total, the architecture has 36 convolutional layers of 3x3 and stride 2 structured in 14 modules that, except for the two extremes, have residual linear connections around them.

The advantages and outperforming of solving computer-vision tasks through deep learning techniques have been demonstrated in the literature during the last decade. However, to obtain high performances using deep learning, large amounts of data (with the corresponding label or ground truth) are needed. To mitigate this requirement, transfer learning technique was proposed by Bengio [157] and Yosinski et al. [158]. This methodology consists in using the knowledge of models with large databases that have already been pretrained on other occasions, and using the weights obtained to train new classification models with a smaller amount of data. An example of this is ImageNet dataset, which has more than 14 million images belonging to 1000 different classes and whose weights obtained are available to the general public. This technique makes possible to use the aforementioned CNN architectures to be retrained for solving specific image classification tasks.

6.4.2. Object detection

Object detection is the first step in scene description. This task consists in locating elements within an image, as well as determining which class it is part of. In this way, it is possible to differentiate into two types: detection of single objects and detection of multiple objects.

Before the arrival of deep learning, object detection was based on an accurate detection of objects. Bounding boxes running through the image were able to generate a series of candidate regions. In parallel, using feature extraction and classification techniques the content of the candidate regions was identified to determine to the object class [159].

CNNs were ground-breaking in this task. Girshick et al. [160] treated each region as a convolutional neural network (R-CNN) to obtain a fixed-length vector from each, which will be input into support vector machines (SVM) to classify the object. Wang et al. [161] presented a similar approach based on proposals of object regions called regionlets, which use features such as local binary patterns, gradient dense histogram, shallow CNN and covariance among others to discern the type of object. A different approach is to use multi-scale deformable part model (DPM) instead of proposing search regions within the image. Ouyang et al. [162] proposed DeepID-Net, where deformable CNNs are used by adding a def-pooling layer to model the deformation of parts of the object. Regarding to the recognition of fine-grained objects, their classification is more difficult because the differences between categories are much subtler. For this reason, Huang et al. [163] proposed a progressive location of pieces, in which they combined the part of detection of pieces and the part of classification of objects together. Then, it would be progressively refined with a SPP-Net pooling layer, which makes it possible to identify more distinctive features that help to obtain a better classification of the object. DeepMultiBox [164], trained with ImageNet, follows an approach based on prominent objects in an image, where prominent parts of objects are detected by removing the image background. Overfeat [165], is a hybrid model that combines saliencіality and multi-scale models, which performs classification, localization and detection simultaneously on the same shared network. In the Markov random field model proposed in [166], an iterative sequential location is used to position and punctuate the bounding box. A multiscale volume model is created, resulting from the combination of context modelling and multiscale structure for object detection and location.

The last advances in object detection by using deep-learning techniques allows to reduce computational time in order to perform real-time object detection (i.e. object tracking). In particular, Girshick et al [167] added a new pooling layer to the R-CNN to locate the region of interest (RoI) which allowed it to significantly improve the speed of training and testing without a major impact on accuracy. In addition, a network of fully convolutional proposed regions [168]was added to determine the class to which the object belongs while detecting where it is located. This type of network is known as Faster-R-CNN. The fact of being able to detect objects at high speeds, allows the recognition of multiple objects in real time. The YOLO (You Only Look Once) technique [169] is the most used for this purpose. In YOLO, the object detection problem is modelled as a regression problem. In this case, instead of iteratively browsing the image by searching regions and evaluating probabilities, the image is scanned only once throughout the training and testing processes and from there the information is inferred, saving a lot of computational cost.

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6.4.3. Content generation

Deep learning models usually require a large amount of data to work properly. However, it is usually common not to have all the necessary data. For this reason, generative models arise, capable of being trained with missing data. These models can understand the essence of the data and estimate the distribution that best represents it, in order to be able to generate new samples if desired [170].

For the implementation of generative models, the most representative networks are known as GAN, Generative Adversial Nets, which have experienced great growth since they were proposed in 2014 [171]. In this first proposal, Goodfellow et al. developed a generative model based on the simultaneous training of two models, one of them generative and the other discriminative, the latter in charge of studying the probability that one sample comes from the generative model or from the real training set. The generative model does not have any direct contact with the real samples, but instead knows them from the interaction with the discriminator. Then, Goodfellow made a tutorial where he explains how a GAN work and the advantages and disadvantages of working with GANs instead other models [172]. The GAN can be used in a wide range of applications within the field of computer vision such as object detection [173], image captioning [174], and natural language processing [175]–[177] (although it has some limitations [175]) and even for image editing [178], among others.

The first GAN [171], consisted of a fully connected neural network, applicable to simple images and databases such as CIFAR10 and MNIST. Later, other alternatives where proposed like fully convolutional neural networks. In [179], Randford et al. proposed a deep convolutional GAN (DCGAN) for both, generator and discriminator, which pleasantly perform unsupervised learning. This type of networks represented a great advance in the generation of images. In this same document, they demonstrated that the performance of the discriminator is superior if Leaky RELU is applied as activation functions between the intermediate layers of the discriminator. In case of having samples represented in 3D, Wu et al. [180] incorporated volumetric convolutions to the GAN, and that it is useful for learning in both 2D and 3D images. In the 2D framework, Mirza et al. [181] presented a conditional version of the GAN, conditioning the generator and discriminator network, offering a better representation for multi-mode data generation. Originally, GANs cannot map a data in a latent space vector, also called inference. To make this possible, Dumoulin et al. [182] presented an adverse inference model that learns together with the generation network, so that it assigns variables from latent space to the data and the first, data samples to the latent space, producing a discriminatory network with an encoder that learns from the inference network.

After completing GAN training, the neural network can be reused for later tasks. For example, the outputs of the convolutional discriminator layers can be used as a feature extractor, exercising the classification function in semi-supervised learning, as proposed by Salimans et al. [183]. Another example of a classifier is the one proposed in [179]. Randford et al. used the GANs as a feature extractor for the classification of the CIFAR-10 database; at the exit of the maxpooling layer they had a 4x4 spatial grid that becomes a vector after passing through the flatten and concatenation phase. This vector is introduced into a regularized linear L2-SVM to proceed with classification. One of the drawbacks of working with synthetic data is the limitation of generalizing to all real images. In an attempt to address this issue, Bousmails et al. [184] proposed an unsupervised GAN model that adapts the images of the source domain (its pixels) so that they appear to be extracted from the destination domain, thus achieving generalization.

In addition, GANs can also be used to refine synthetic images. Shrivastava et al. [185] proposed a simulated and unsupervised learning with unlabelled real data and preserving the annotation information of the simulator, using synthetic images as inputs. As a result, they got a simulator capable of estimating gaze and pose. In terms of image generation, we should mention the model proposed by Denton et al. [186], which used a cascade of convolutional networks (convnets) within a pyramidal Laplacian network, also extending the conditional version of the GANs. This allowed them to present a model where high-quality images of natural pictures are produced from samples of CIFAR10, STL10 and LSUN. Finally, for high resolution images, Leding et al. [187] proposed a super-resolution GAN (SRGAN). In it, a perceptual loss function is added, consisting of loss of content and adverse loss. This was the first network that allows inferring photo-realistic images, performing a 4x scale magnification factor.

6.4.4. Image and video captioning

In a completely digital age such as the present, videos or sequences of images make up a rich and complex source of information. For most human beings, visualizing a short video or scene and describing what happens in it using words is a very simple task. In the case of machines, extracting visual information from the pixels of a video and automatically generating a descriptive phrase is a highly complex problem.

However, computer-vision techniques are currently gaining great relevance in a multitude of scenarios. The transfer of visual information to a machine, with the objective that it will be capable of imitating certain cognitive processes of the human being, gives these techniques a high applicability in countless fields. One of the fields covered by computer-vision techniques is known as Image & video captioning. This name defines the process of automatically transferring the information contained in an image or a sequence of images to a phrase in natural language, i.e. any language understandable by humans.

The ability to describe videos automatically is susceptible to numerous relevant applications such as the classification of images and/or videos based on their content, the textual summary of image sequences for the advertising field, or video surveillance among many others.

The core of automatic video description consists of three clearly differentiated major stages: object recognition, activity recognition, and surface realization. The first works focused on the description of data using natural language focused their efforts on the static image [188]–[191]. These works are based on various algorithms and techniques for the recognition of objects in images and the generation of textual sentences from simple templates. These methods were extended to video description in [192]–[197]. They carry out the description of environments in very specific domains (e.g. kitchen, school, etc.) covering in a very limited way the vocabularies and activities of each specific domain and without the capacity to generalize. The progress of the technique Image & video captioning with capacity of generalization, indistinctly of the domain in which the content to describe is based (open-domain videos), is limited by the great number of existing vocabularies and by the scarcity of annotated data (videos with their respective textual descriptions). The first works in which a description of a small set of open-domain videos was presented were proposed by [198]–[200]. In these works, the techniques of visual recognition from the frames of the video are combined with linguistic knowledge. More specifically, different classifiers are trained to identify hundreds of objects, activities and scenes individually. Subsequently, making use of the classification probability together with knowledge extracted from a linguistic corpus, the best prediction subject-verb-object-scene is estimated.

The development of deep learning and recurrent neural networks led to a noticeable increase in work on static image description using natural language, achieving excellent results [201]–[208]. However, video description has not been the object of so much research and only some works can be found in

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relation to the technique of video captioning through deep neural networks. More specifically, in [209]the authors propose the use of a CNN, to extract visual information from the frames of a video, concatenated with an RNN based on Long Short Term Memory (LSTM) units capable of learning to describe sequences of images. Due to the great limitation of annotated videos, that is, the scarcity of videos with their corresponding descriptive sentence, the authors of [209] propose a training based on image-description pairs for learning. Later, making use of transfer learning techniques and databases for video captioning (video-description couples) give the automatic models the ability to describe sequences of images. Based on this work, Venugopalan et al. modified the design of the network architecture in [210], in order to capture the existing dependencies in a sequence of images and in the corresponding sequence of words that make up the descriptive phrase. Finally, this system includes linguistic knowledge to improve both the grammatical and descriptive quality of the videos [211].

6.4.5. Emotion recognition

In recent years, facial recognition of emotions is gaining importance given the influence it has on communication and interaction between people, as well as in other applications such as virtual reality [212] and driving assistance systems [213], where artificial intelligence is a key tool for its realization.

Generally, facial emotion recognition (FER) is performed in three phases [214]. The first consists of detecting the face and marking its reference points (mainly eyebrows, nose and mouth), then proceeds to the extraction of features and ends by classifying the expression of the person. Additionally, it is necessary to add a distinction between static images and temporal sequences (video) since the latter have to include a space-time component that detects the different expressions throughout the sequence, creating a dynamic variable that stores the displacement between landmarks when the images pass [215], [216].

Before the arrival of deep learning, various methods have been used for the recognition of emotions. The difference between them is the type of features extracted from the face. On the one hand, there exist a bulk of works in which the authors construct the training vector with geometric variables. As can be seen in [217], Ghimire and Lee used the position of landmarks points and the angle formed between them to determine variations between these positions in different images of a sequence, creating training vectors and then classify the facial expression using a SVM classifier or multi-class AdaBoost, comparing it with the prototype facial expression. On the other hand, there exist another work stream based on the extraction of appearance features from several facial regions. To detect which regions are important, Ghimire et al. [218] used an incremental search algorithm; while Happy et al. [219] created the characteristics vector with a local binary pattern histogram of several blocks of a facial region to later proceed to their classification.

With the introduction of deep learning, the use of convolutional neural networks (CNN) is the most common solution for this task [220]. Jung et al. [221] applied this technique for the recognition of FE in images. For this purpose, they used a CNN with facial geometric properties and another CNN with appearance features, obtaining the FER of seven different emotions with the combination of both networks, using the CK+ and MMI databases in their training. Additionally, Zhao et al. [222] proposed a layer capable of inducing facial regions with relevant information using feed-forward as a recognition algorithm, and which they called deep region and multi-label learning (DRML).

The aforementioned methods were proposed for static image and they do not allow facial recognition of emotions in a video sequence. For this purpose, recurrent neural network with long and short term memory units, known as LSTM, is used. This kind of neural network is capable of storing information of the temporal variable, which is combined with the spatial features recognized by CNNs. In the EmotiW Challenge of 2015, a contest for the recognition of emotions in nature, specializing in facial expressions, Kahou et al. [223] presented a hybrid model of analysis of seven emotions that combines CNN with RNN performing temporal averages of aggregation. As a result, they obtained better recognition results than those previously proposed without RNN.

6.4.6. Reinforcement learning

Reinforcement learning (RL) is a technique in which the intelligent system learns to behave from the sampling and explotation of its environment and uses what it learns to find better ways through trial and error procedures. The system does not have information about which action will be the next one but after performing a series of actions, it will receive certain rewards, and since its objective is to maximize these rewards, it will learn to choose the following actions thanks to the best previous rewards, obtained from trial and error [224].

In the literature there are also references to the RL as the search for balance between exploration and exploitation because the device has to prefer past actions that it knows produce great rewards (exploitation), but it also has to test new actions that are unknown (exploration) to see if they are rewarding or not [225].

Traditionally this methodology has been very useful especially in game agents, whether video games or board games. Specifically, Mnih et al. [226], applied convolutional neural networks to Atari games in the Arcade Learning environment. Their model consists of a variant of Q-learning from which is obtained the function of estimated rewards from rows of unprocessed input pixels.

For board games, Go is the most investigated with artificial intelligence because the board offers a great variety of possible movements. In this context, RL is perhaps the most exploited alternative given the reward function that the system receives. Silver et al. [89], proposed a different approach to this game using deep neural networks in which they combined reinforcement learning of single-player games along with supervised learning from expert human play, given rise to the famous AlphaGo, the first intelligent agent that beat the best human Go player at the time.

In other different areas, the reward function is more difficult to obtain given the difficulty of raising all possible scenarios, as well as leaving the system to experiment based on proof of error in all of them. This is the case of medicine and driving, where no errors are allowed. Specifically, in the case of medicine it is necessary for agents to make use of *off-policy evaluation*, which consists in learning from a collection of historical data. This technique can be put into practice using Q-learning for the implementation of Reinforcement learning algorithms [227]. However, other authors, such as Gottesman et al. [228], point out that using off-policy evaluation to learn the correct policy can be difficult, so the data must be treated with finesse since, for example, there are collections of data taken from patients medicated with a certain drug, but not from patients not treated with it.

In other areas such as driving, Abbeel et al. [229] proposed a model which they called "Inverse reinforcement learning". The main idea arises from the difficulty of contemplating all possible scenarios, so instead of giving the system its own reward function, it is pretended that the system

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learns from the observation of an expert performing the same task, and thereby extracting the reward function.

6.4.7. Natural Language Processing

Natural language processing is present in a variety of applications of everyday life, such as automatic correction, suggestions to answer emails, machine translation and voice recognition among many others.

One of the first models designed for natural language processing was developed in 2001 by Bengio et al. [230], known as the neural language model. The mission of this model was very simple; from a series of given words, the model had to predict the next word, using a neural network with feed-forward connections. The preceding words represented in vector form (word incrustations) were concatenated and introduced into a hidden layer connected to a subsequent softmax layer.

Language modelling is defined as predictive learning and it is at the core of many later developments, including sequence by sequence models, word inlays or pre-learned language models among many others [231]. In order to achieve a total understanding of natural language, it is not enough to learn from the elementary form of the text, but it is necessary to apply new methods.

A way to make language learning faster is to train the models to perform multiple tasks, linking the weights obtained in the different layers of the network. This concept called multitask learning (MTL) was first proposed in 1993 by Rich Caruana [232], under the idea that working with isolated tasks is neglecting the inductive bias inherent in similar tasks so that the use of multiple tasks would obtain a source of inductive bias between them. This fact speeds up the learning process and allows more complex tasks to be carried out. In the NLP environment, MTL was not applied until 2008 by Wetson and Collobert [233], who designed a convolutional neuronal architecture trained with weight sharing, a specific type of MTL with semi-supervised learning. Multi-task learning is currently employed in a multitude of NLP tasks and, as models are evaluated, it gains more prominence, with specific reference points for this type of learning having recently been proposed [234].

In 2013, Mikolov et al. proposed in [235] two new architectures for calculating more efficient continuous vector representations of words from large data sets, removing the hidden network layer and approximating the target. This change along with the implementation of word2vec, increased the word embedding capacity. Word2vec, allows predicting a central word from surrounding words (CBOW) or capturing a large number of syntactic and semantic inter-word relationships providing great quality to the prediction (skip-gram) [236]. The broad training of these networks allows them to find linear relationships between words by attending, for example, to their verbal tense or gender [237], [238]. Later, in [239] Bolukbasi et al. began to perform incrustations of words pre-learned as initializers, under the idea that the widespread use of word incrustations may amplify the bias of the data and thus improve the performance of the rest of the tasks. The vector representations provided by word2vec can also be learned by matrix factorization, such as SVD and LSA [240]; however, word2vec remains a popular and widely used option today. These word embeddings can also be done with terms from different languages, as transfer between different languages is allowed. This feature is widely used in unsupervised machine translation applications [241], [242].
Convolutional neural networks are widely used in NLP. The representative work of Kalchbrenner et al. [243] described a dynamic CNN with a layer of dynamic k-Max pooling applied to linear sequences, and where the lengths of the input phrases are different. In the text area, CNNs only work in two dimensions and filters only work in the temporal dimension. Both RNN and CNN model language as

sequences from left to right, although linguistically the language is hierarchical, that is, the text is made up of phrases, which is also made up of words. For this reason, appear recursive neural networks [244], hierarchized from bottom to top like a tree.

In 2014, sequence by sequence learning was proposed, by the hand of Sutskever et al [245]. For its implementation, a neural network (usually RNN) is required to act as an encoder, treating each sentence symbol by symbol and converting it into a vector so that, at the output, another neural network (usually also RNN) decodes and predicts the symbol at the output. This is the technique used in natural language generation tasks, as well as in machine translation. Its main limitation is that it is required to compress the entire content of the sequence in a vector of fixed size. In order to avoid this, attention appears [246], which allows the decoder to look at the hidden states of the source sequence, and thus provide an additional input to the decoder, which will be the weighted average of these hidden states. This technique also allows, among other things, to obtain words within a given context so it is common to find it in reading comprehension [247], although it is especially adopted by the Neural Machine Translation (NMT) [248]. Afterwards, models appeared with explicit memory capable of retaining information for longer periods of time and in which it can be read and written. These memories do not depend on the hidden states of the past but on the present state. Examples of such models may include Memory Networks [249] end-to-end memory networks, neural Turing machines, and neural differentiable computer [250]. Note that in 2017 and 2018, various supervised tasks have been used to pre-train neural networks [251] although, when it comes to linguistic models, pre-configured word embeddings are only used in the first layer. Language model inlays can be added as features to other models, thus providing an improvement in many different tasks [252], especially when little data is available for training.

6.4.8. Sentiment Analysis

Sentiment analysis consists in extracting subjective information from text or spoken language, identifying feelings, emotions and opinions [253]. It is common to use it in used in various applications covering from business purposes to applications oriented in human behaviour understanding [254].

Focusing on text analysis, it is necessary to determine the polarity of the text before classifying a sentiment present in a writing, which can be positive, negative or neutral. For this reason, this practice is also known as opinion mining [255]. SA can be divided into three levels depending on the fragment of text analysed. Firstly, there is the document level, where the global text will be classified according to its polarity [256]. If this classification is done in sentences, we would be at the sentence level [257], which distinguishes between objective and subjective sentences. And finally, for a fine-grained analysis we would be at the aspect level centred on the type of language used [258].

Sentiment analysis requires the use of natural language processing techniques, structured and unstructured data mining, retrieval information and other computational and text analysis techniques. [259]. For the classification of feelings, the information in the overall text should be reflected in smaller representations like phrases and words. At the beginning, the word bag model (BoW) [260] was used, which converts a text into a fixed-length vector, a technique also used in NLP. However, BoW ignores the order of the words and their semantic characteristics, so in some research it has been replaced by word embedding techniques. From that vectors, it is now possible to establish a SA classification based on three approaches [255]: lexicon based, which assumes that the collective polarity of a sentence or document is the sum of the polarities of the individual phrases or words, machine learning and hybrid approaches that combine the previous two.

In 2002, Pang and Lee [261] were pioneers in applying the area of sentiment analysis. The activity is based on classifying binary sentiments from film reviews, for which they also applied maximum entropy (ME), naïve bayes (NB) and SVM techniques. These techniques continued to be used in other investigations reaching different levels of precision, as can be observed in [262], [263]. Dang et al. [264] used SVM for classification, using Gain of Information (GI) to select characteristics and thus increasing the effectiveness of the model. McDonald et al. [265] based their work on classifying the text at different levels of granularity, specifically at the document and sentence levels. They considered both levels and the interdependence between them, because the classification of one level influences the other. They used classification techniques ensuring that the solutions were consistent, for which they applied Viterbi programming that allowed them to reduce the classification error. Moraes et al. [266] performed for the first time an empirical comparison between SVM and artificial neural networks, proving that, except for the case of unbalanced data, the ANN classification results were equal to or superior to those of SVM.

In the case of unsupervised learning, Le and Mikolov [236] proposed a paragraph vector that learns from the characteristics of fixed-length vectors, predicting the surrounding words present in texts of variable length, whether complete documents, paragraphs or sentences. Ghiassi et al. [267] incorporated a supervised reduction of n-grams characteristics, which reduced the complexity of the model and improved the precision of the classification carried out with SVM. Later, they used the automatic learning algorithm DAN2 (dynamic artificial neural network) for the classification, thus giving a greater precision to the model than that obtained with SVM.

A model based on CNNs was proposed in [260] by Zhang et al. which uses convolution layers to perform the conversion of the fixed-length vector (BoW). For the analysis of sentiments at the aspect level, Ruder et al. [268] worked with word embeddings and incorporated a bi-directional short-term memory to enhance relationships between the sentences themselves and with the rest of the sentences. Yang et al. [269] proposed a model that made use of attention at both the word level and the sentence level, which made it possible to adapt the level of attention given to individual words or phrases when predicting.

6.5. Cognitive computing and expert systems

The term cognitive systems arises in 1990, considered as an evolution of artificial intelligence, whose contribution lies in teaching computers to imitate the way the human mind works and to be able to learn from experience, instead of being merely an artificial system [85].

Cognitive systems, therefore, require a high level of natural language processing so that they can semantically understand the information provided by the environment around them and be capable of storing and processing a large amount of data from several sources [270], in order to be able to respond to multiple scenarios. Moreover, as the information and variables they demand are continually changing over time, they require their learning to be adaptive to suit each situation [271].

For this purpose, intelligent computers are equipped with advanced navigation, detection and visualization systems that allow them to act in a proactive way, thus favouring human-computer iteration, helping humans in a great variety of applications of daily life. Cognitive computing can contribute in the same way to the increase of productivity since on one side it offers assistance to people to carry out their tasks more efficiently, while on the other side they can reach a thought speed even higher than the speed of the human mind.

There are four techniques for making these measurements. One of them consists of that the subject evaluates his or her own performance with feedback from the ratings given. Another type of measurement is task-based, which evaluates the performance of the subject in each task performed. To these two are added analytical techniques that determine specific aspects of human performance with empirical data; and psychophysiological measures, which use senses to measure empirical data from the subjects [16].

Analytical models are used to model and simulate the first stages of the design, before moving into the human in the loop phase. By taking the required measurements in that phase, both of the system and of the human, these are used to improve the analytical model, completing a cycle. In Figure 13, this cycle can be visualized with the measurements made in each phase.

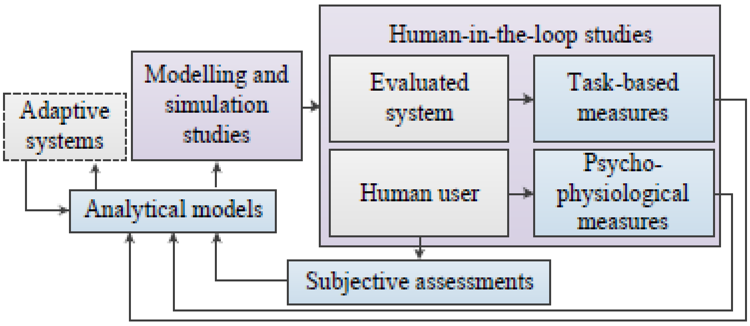

Figure 13. Interactions between the different human performance assessment techniques [16].

A large number of applications can be found for these cognitive systems and in multiple activity sectors, most of them focused on helping human beings.

One application is the cognitive camera, whose objective is to replicate human vision to, for example, introduce them into vehicles and help them park and even send a warning signal to the distracted driver who does not pay attention to the road [272], [273].

In the area of the industry, and production in general, providing cognitive capabilities to current systems can help to deal with the problem of changing market demand and the control of quality and cost of products, or even responding to growing personalized demand [274], [275]. In addition, these systems can also be incorporated into materials, so that both engineers and consumers are aware of the state of their properties and cognitive capabilities, in other words, of how the material "feels" [276].

Another application in which the research is being carried out is the creation of robots with cognitive brains and consequently greater autonomy than the current ones, which can act as human's co-workers [277].

In the automotive sector, cognitive cars are also relevant. These incorporate sensors such as voice recognition, cameras and navigation devices that provide continuous information to the car and encourage it to think like the human who drives it, and thus be able to help him. The main reason for the development of these cars is the protection of all passengers, as well as road safety in general. For

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this reason, there are also autonomous cars with cognitive capabilities, which are able to make decisions autonomously at any moment [125], [278].

Cognitive computing is also useful in the field of aviation, since it can contribute to improve and make early detection, assessment and decisions in complex situations, whether due to the conditions of the environment through which aircraft and air traffic circulate or due to the management of the system's faults, and even those coming from humans; encouraging greater air safety [279], [280].

7. Adaptive/Cognitive HMI

7.1. General Review

The Human-Machine System (HMS) has three components; in the field of cockpit a human operator (the pilot), a machine (the aircraft) and the interface that allows them to communicate. The interface is traditionally the means through which the humans interact with the machine. The HMS describes the combination of the human and the machine. With the advance of computing technologies, the capabilities of modern aircraft have significantly increased during the past decades.

HMS can be passive or active. Passive HMS limit human interaction with the machine and usually involves conventional human machine interfaces (HMI). Active HMS means that the machine is designed to provide intelligent and adaptive assistance. An intelligent adaptive system (IAS) in the cockpit will promote the interaction between human and machine to achieve a 'common goal' similar to what happens between a pilot and a co-pilot.

7.2. Cockpit Assistants

Assistive technologies are already interacting with the pilots (pilot and co-pilot) in order to increase the safety of the flight and improving the overall conduct of the machine.

Figure 14. Flight Director

Systems like flight director (FD cf. Figure 14) which guide the pilot, flight management system (FMS cf. Figure 15) enable the aircraft to fly itself most of the time, safety nets like GPWS (ground proximity warning system), TCAS (traffic collision avoidance system cf. Figure 16) can help pilots to detect and avoid a ground or aircraft collision. For instance, the TCAS offers traffic detection alerts (TA) in the vicinity of the aircraft but also proposes resolution advisories (RA) (change of altitude) whenever there is a collision risk. These TA and RA are being said aloud ('traffic traffic' 'climb climb') by the TCAS system like a human could do.

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Figure 15. Flight Management System

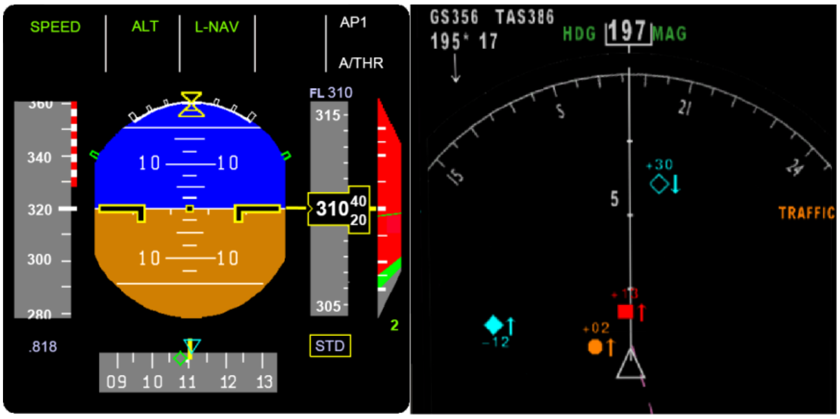

Figure 16. TCAS Traffic Alert and Resolution Advisory

Voice or audio enhanced systems are numerous in the cockpit, GPWS, TCAS, wind shear warning, flight envelope protection.

7.3. Adaptable, intelligent and adaptive HMI

HMI is all the means by which humans interact with the HMS, it is a part of the HMS. HMI can cover a screen a keyboard, a mouse. In the case of a glass cockpit, FCU, MCDU, PFD, ND, yoke are part of the HMI. There are multiple ways to design an HMI, usually a task model of actions performed by an operator is being used. This task model will help to define how the machine will support the human to achieve goals associated to the task. This approach is technology centred and more focused on the machine than the human.

Adaptive and intelligent HMI not only focus on task model but also on user model. That is to say that, understanding human abilities and limitations, the HMS designer will try to build an effective HMI that will improve the assistance provided to the operator. An intelligent interface can be defined as "an interface where the appearance, function or content of the interface can be changed by the interface itself in response to user's interaction" [281]. This assumption means that the adaptation and the reason why it occurs is embedded in the HMS design. Adaptive HMI purpose is slightly different than intelligent HMI. Tomlinson, Baumer & al. [282] propose this definition "Adaptive interfaces are interfaces that seek to predict what sorts of features would be desirable". It means that the layout of the HMI could be changed dynamically according to those predictions. Adaptable HMIs are customizable by the user before or during activity. Several studies show that adaptive HMIs may hinder the interaction and users are more comfortable with static and adaptable HMIs [283]–[285]. Intelligent and adaptive HMI are both based on a user centric design approach.

In order to build and maintaining a good situation awareness (SA) - SA is defined as 'the perception of the elements in the environment within a volume of space and time, the comprehension of their meaning, the projection of their status into the near future and the prediction of how various actions will affect the fulfilment of one's goal' [286] - a cognitive engineering approach lead several team to develop cognitive assistance systems (CAS) for the cockpit. A CAS takes into account the limitations of humans to optimize information presentation and automation during task. It needs to 'understand' the situation as humans do and know the state of the user to prevent SA enemies. Augmented cognition (interdisciplinary field with hci psychology ergonomics and neurosciences) and neuro-ergonomics (application of neurosciences to ergonomics) emerged in the early 2000.

In the cockpit, CAS have been developed since 1999 with CASSY (Cognitive ASsistant SYstem) and COGPIT (COGnitive cockPIT [287]). The latter has been studied by the DERA (United Kingdom Defence Evaluation and Research Agency), they describe a level of automation taxonomy the Pilot Authorization and Control of Tasks (PACT) and their cognitive cockpit systems for military aircraft. COGPIT has three main functional modules, COGMON (cognition monitor), SASS (situation assessor), TIM (tasking interface manager). COGMON is based on real time analysis of psycho-physiological and behavioural states of the pilot (workload, arousal). SASS provides information related to real time analysis of the mission and support decision making. TIM takes information coming from COGMON and SASS in order to optimize the means by which information is communicated to the pilot.

Recent work at ISAE-SUPAERO has been done on the topic using eye tracking in the cockpit to detect the 'non-perception' of relevant information in real time.

Some consideration related to the implementation of CHMI is addressed in [279], where a tentative layout is proposed (see Figure 17). The system comprises 3 major systems: Human performance module, task management module and adaption engine. The objective of **Human Performance Module** is to assess the human operator using specific human performance models in order to estimate human performance and cognitive states. There exit four broad techniques for assessing human performance: Subjective assessments, task-based metrics, analytical techniques and psycho-physiological measures. On the other hand, the **Task Management Module** monitors the external environment and on-board systems parameters, prioritizing and tracking the progress of current tasks, as well as planning and schedule future tasks. And the **Adaptation Engine** receive inputs from the modules mentioned before and reconfigures de HMI according to a set of decision logics stored in decisions tables.

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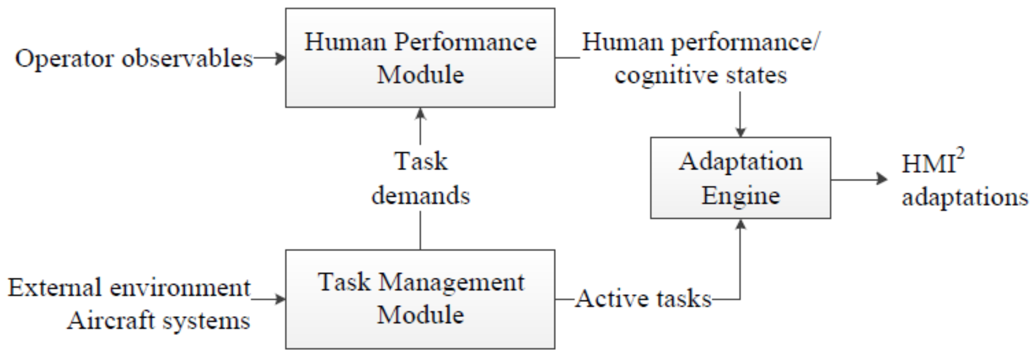

Figure 17: General layout of adaptive HMI in [279].

Other researches such as [16] proposes a more detailed architecture for the implementation of this CHMI. "The CHMI utilises psycho-physiological sensors, which are integrated into the flight deck, to monitor the pilot in real-time. Cognition models are used to assess the pilot's cognitive states, such as fatigue, stress, attention and mental workload based on the physiological data collected. Important physiological indicators include brain (e.g., blood oxygenation levels), cardiac (e.g., Heart Rate (HR), Heart Rate Variability (HRV)) and eye (e.g., blink rate, eye movements and pupil diameter) activity. Brain activity provides information on cognitive workload and can be tracked either electrically (via electroencephalography (EEG)) or optically (via functional near-infrared (fNIR) spectroscopy). Cardiac activity can be measured with wearable devices such as wristbands or smart shirts and is utilised to assess stress and workload of the pilot. Eye activity can be tracked remotely with multi-camera systems and is also a good indicator of workload – blink rates and duration are inversely correlated and decrease with increasing workload [288]. Additionally, pilot attention can be modelled from gaze patterns, which are correlated with information sampling [289].

An inference engine is used to manage task distribution between the automation systems (e.g., NG-FMS) and human operators (air- and ground-based) based on the external environment and their cognitive state. If a high single-pilot workload is assessed, the CHMI provides support by suggesting a transition to higher levels of system automation, reduces screen clutter, and/or transferring non-critical tasks to the ground crew. On the other hand, if the system infers that the pilot is losing situational awareness at a high level of automation, the CHMI either suggests a more suitable level of automation or triggers appropriate alerts to keep the pilot in the loop. Adaptive alerting is designed to provide cues that complement the cognitive state of the pilot, based on the system's assessment of the situation. Alerts are prioritised and are provided through a combination of visual, auditory and haptic feedback; multi-sensory feedback increases the pilot's perceptual bandwidth with more channels to process information." [16] Figure 18 illustrates the architecture of the CHMI.

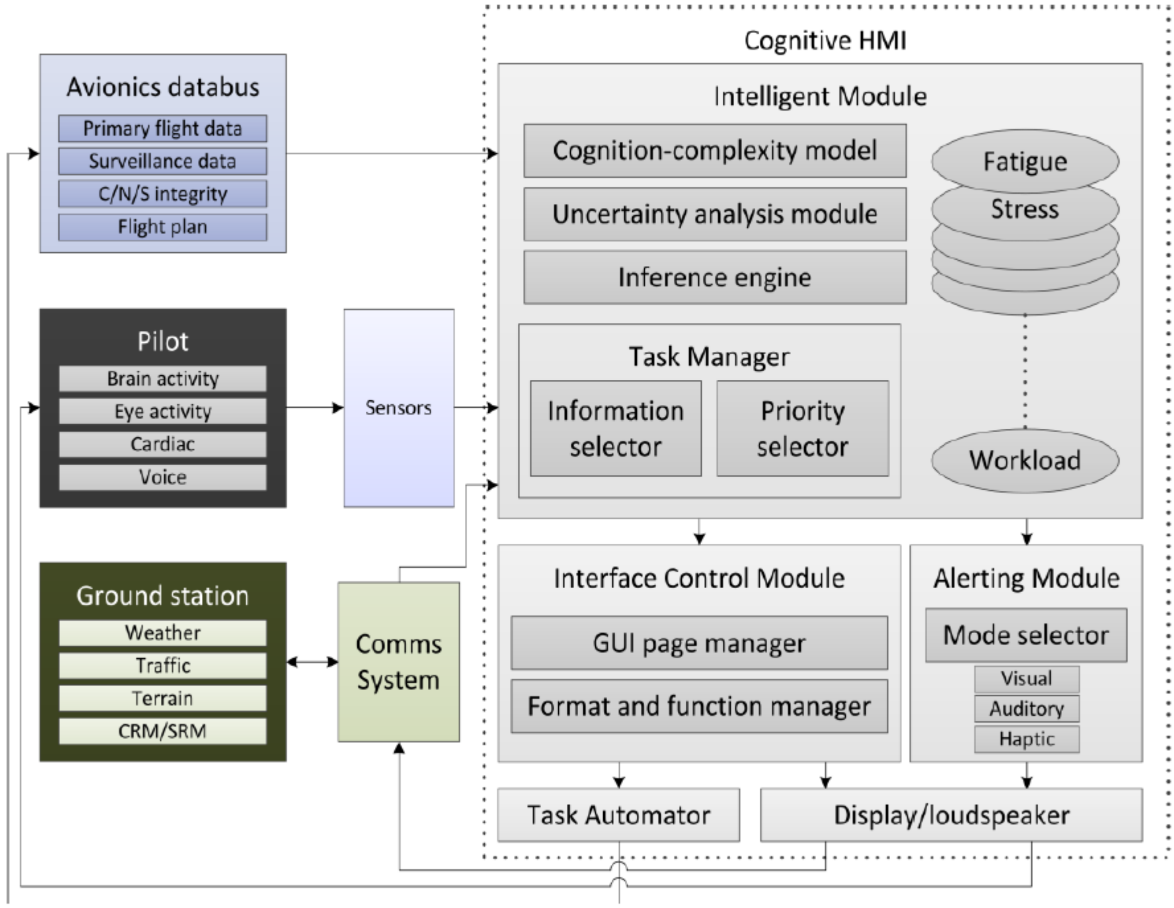

Figure 18. Cognitive HMI architecture [16].

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8. Virtual Pilot Assistant architecture

Most of the reviewed literature agrees that for the SPO it is necessary the implementation of a VPA. Figure 19 shows the proposal of [16], in which highlights 4 major systems: communications, surveillance, flight management / control and Human Machine Interfaces (HMI) systems.

“The communications system enables data-sharing between the single-pilot, GO, AOCO and ATCo via a network comprising various RLOS and BRLOS data links. In case of emergency, a reliable, secure high-speed command and control (C2) link enables the GO to assume direct control of the aircraft’s flight management and control systems. The surveillance system utilises an Airborne Surveillance and Separation Assurance Processing (ASSAP) subsystem, which is integrated into the flight management system, to provide automated Separation Assurance and Collision Avoidance (SA&CA) capabilities. The NG-FMS is interlinked to the Flight Control Unit (FCU), autopilot and Flight Control System (FCS) to provide guidance, navigation and control, as well as trajectory optimisation, planning, negotiation and validation functions. An Integrated Vehicle Health Management (IVHM) subsystem automates the management and monitoring of aircraft systems, providing appropriate updates, warnings or alerts to the pilot (via a cognitive HMI) and the ground crew.” [16] These concepts will be described in the following subsections.

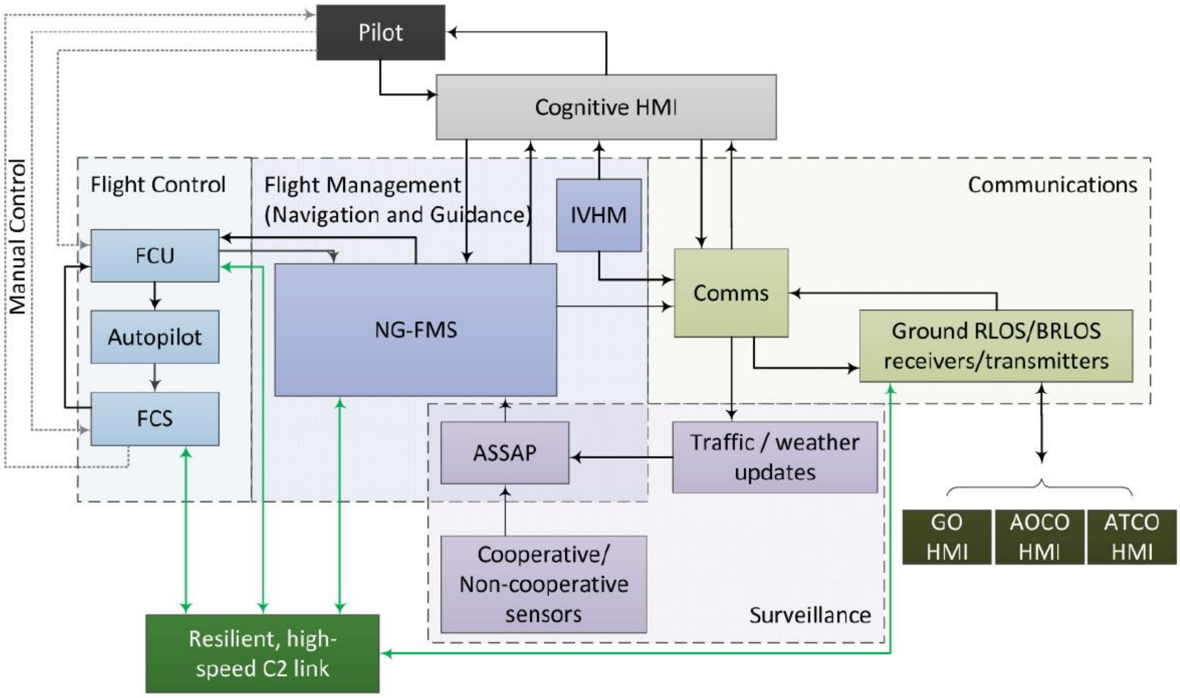

Figure 19. VPA system architecture [16].

8.1. Communications

"Depending on the criticality of information being transferred, different links (with different Required Communication Performance levels) are used to support transfer of data and information between the aircraft and various ground agents. The European Organization for Civil Aviation Equipment (EUROCAE) Working Group 73 (WG-73) has developed a methodology for determining the Required Communications Performance (RCP) for RPAS [290] , based on ICAO's Manual on RCP (Doc 9869) and RPAS (Doc 10019). A similar framework is used to define the Command, Control and Communications (C3) links for SPO for this section. These comprise safety critical, non-safety critical and real-time C2 links, as well as links for ATC and ground crew voice/data communications (Figure 20)." [16].

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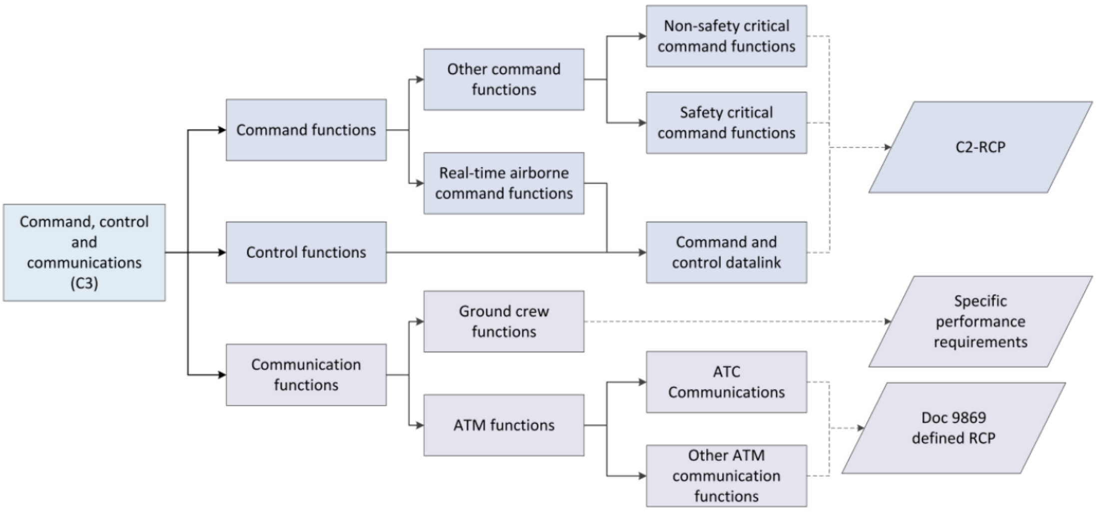

Figure 20. Command, Control and Communications (C3) links VPA system architecture [16].

"The communication links may be within RLOS or BRLOS as depicted in Figure 21. Ground-to-ground links between the ground crew and the ATC provide lower latency and higher reliability than air-to-ground radio links, supporting some information exchange in instances when specific air-to-ground C3 links suffer from degradation for example due to weather, terrain or signal obstruction." [16].

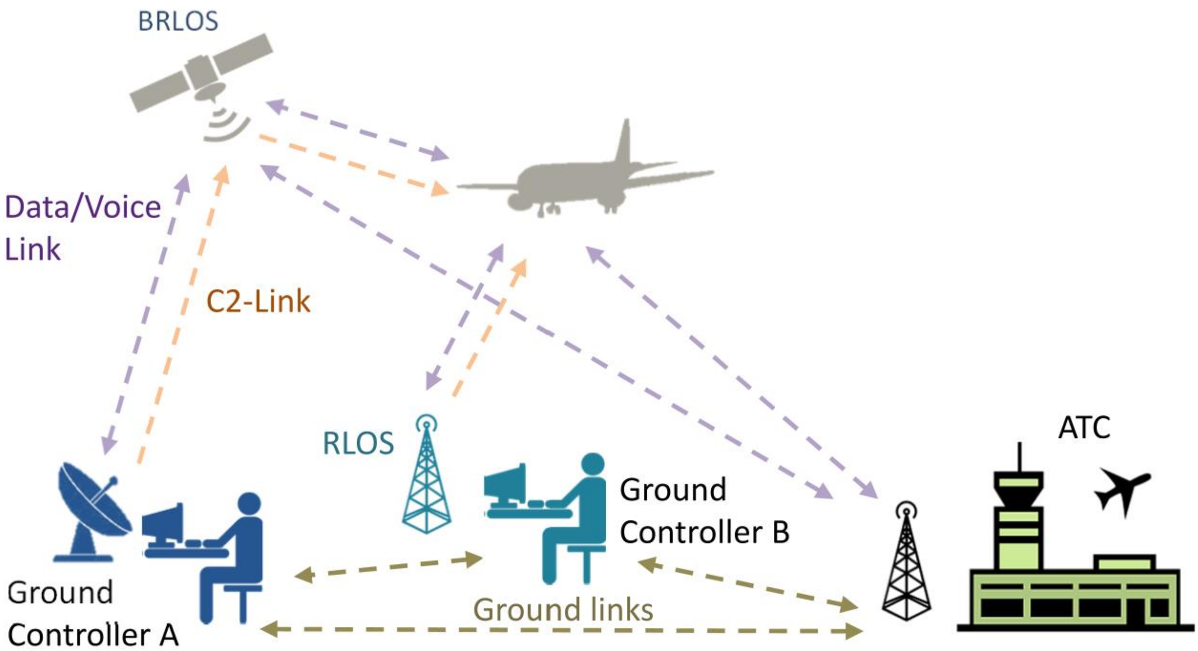

Figure 21. SPO Communications Network [16].

"Evaluating SPO RCP requires consideration of the operational risk in the event of a loss-link. The following factors will affect operational risk: increase in single-pilot workload, information carried by the link, level of autonomous operation, population density in area of operations and SPO operating airspace class. The RCP values for RPAS operations as proposed by WG-73, which are more stringent than manned operations, are shown in the Table 4 [290] . The RCP is defined by the separation between the aircraft and the ground station, as well as the link transaction time. Limits are set for the link continuity (lower transaction time than required time specified by the RCP type), availability (ratio of actual to specified operating time) and integrity (probability of undetected errors in transaction)." [16].

Table 4: RCP for RPAS, from EUROCAE WG-73

RCP Type	Separation (NM)	Transaction time (sec)	Continuity (probability/ flight hour)	Availability (probability/ flight hour)	Integrity (acceptable rate/ flight hour)
RCP 10 Tactical control; Continental Europe	5	10	0.99985	0.999997	1.43x10-6
RCP 60 Routine comms; Continental Europe	5	60	0.99985	0.99999	1.43x10-6
RCP 120	15	120	0.99985	0.99999	1.43x10-6
RCP 240 / RCP 400 Oceanic	30 / 50	240 / 400	0.99985	0.99999 / 0.99988	1.43x10-6

8.2. Surveillance

"On-board surveillance systems provide a combination of surveillance and surveillance-based guidance (through interfacing with the NG-FMS) and alerts to enhance flight safety and decrease single-pilot workload by ensuring autonomous separation assurance and collision avoidance. Surveillance information can be obtained from information services, as well as cooperative and non-cooperative sources. Information services are provided by the ATCo or ground crew and contain information regarding traffic, meteorological or other potential hazards to flight. To allow the same surveillance systems to be deployed in conventional, single-pilot and unmanned aircraft, a unified approach to non-cooperative and cooperative separation assurance and collision avoidance is proposed in Figure 22, adopting a combination of navigation and tracking sensors/systems (such as Global Navigation Satellite Systems (GNSS), Inertial Measurement Unit (IMU) and Vision Based Navigation (VBN) sensors) in the navigation and guidance system architecture. Errors in the obstacle/intruder measurements are estimated considering a combination of non-cooperative sensors, including active/passive Forward-Looking Sensors (FLS) and acoustic sensors, as well as cooperative systems, including Automatic Dependent Surveillance Broadcast (ADS-B) and Traffic Collision Avoidance System (TCAS). In this unified approach, analytical models are implemented for real-time processing of navigation and tracking errors affecting the state measurements allowing a direct translation into a unified range and bearing uncertainty descriptors[291], [292]. An Airborne Surveillance and Separation Assurance Processing (ASSAP) subsystem processes the incoming surveillance information according to the relevant surveillance applications for the single pilot (i.e., violation of separation, resolution advisory, etc.). The ASSAP is integrated into the NG-FMS to provide autonomous separation assurance, tactical re-routing, conflict resolution and/or automatic landing in case of single-pilot overload, incapacitation, and/or loss of C2 link. RTCA DO-289 provides the Minimum Aviation System Performance Standards (MASPS) for surveillance applications, with detailed specifications for the information (data

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content/quality, update interval, latency, coverage, continuity), as well as the transmitting, receiving, ASSAP subsystems and display interfaces.” [16].

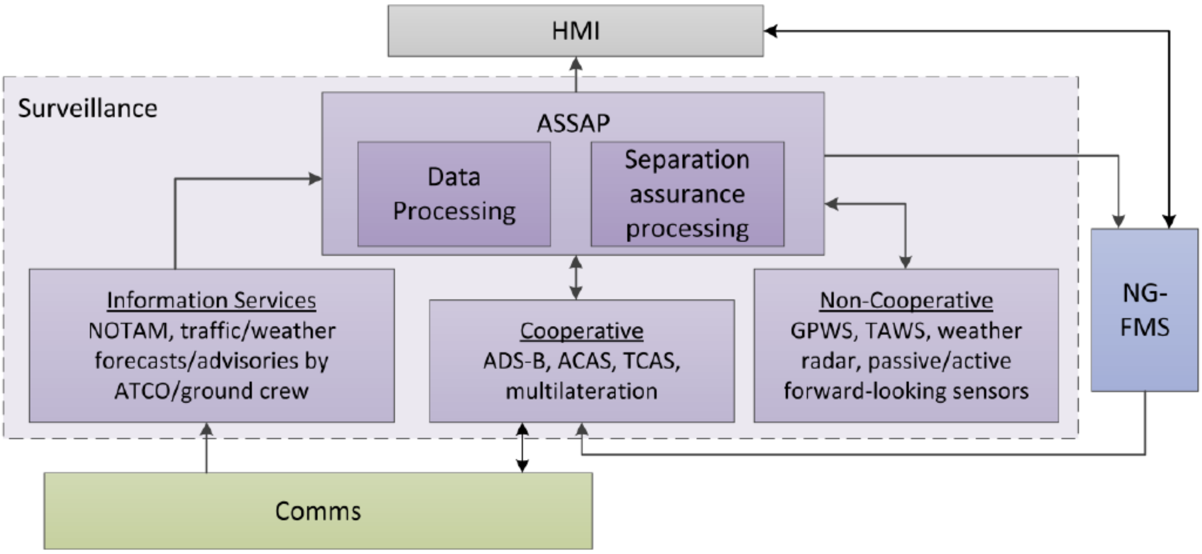

Figure 22. Surveillance Subsystem Architecture [16].

8.3. Flight Management

“To support 4-Dimensional (4D) Trajectory/Intent Based Operations (TBO/IBO) in the future airspace, a Next Generation Flight Management System (NG-FMS) [289] is employed to provide autonomous flight planning, trajectory prediction, performance computations, guidance and control functionalities for manned, single-pilot and unmanned platforms. The NG-FMS (Figure 23) introduces a trajectory planning/optimisation subsystem, which performs multi-objective trajectory optimisation through mathematical algorithms, for strategic, tactical and emergency operations. Information about the flight plan is provided by a navigation subsystem and can be used to correct any deviation of the lateral, vertical and time profile from the intended path. Additionally, optimal trajectory intents are generated based on pre-defined cost functions to minimize fuel consumption, flight time, operative costs, or emissions, under constraints imposed by weather, airspace and traffic (Separation Assurance and Collision Avoidance (SA&CA)) requirements. The process of negotiation involves communicating these intents to the ground crew and ATCo, which are validated before being executed by the NG-FMS. Finally, a CNS integrity manager [23] is used to ensure the required performance levels (RCP, RNP, RSP) are maintained.” [16].

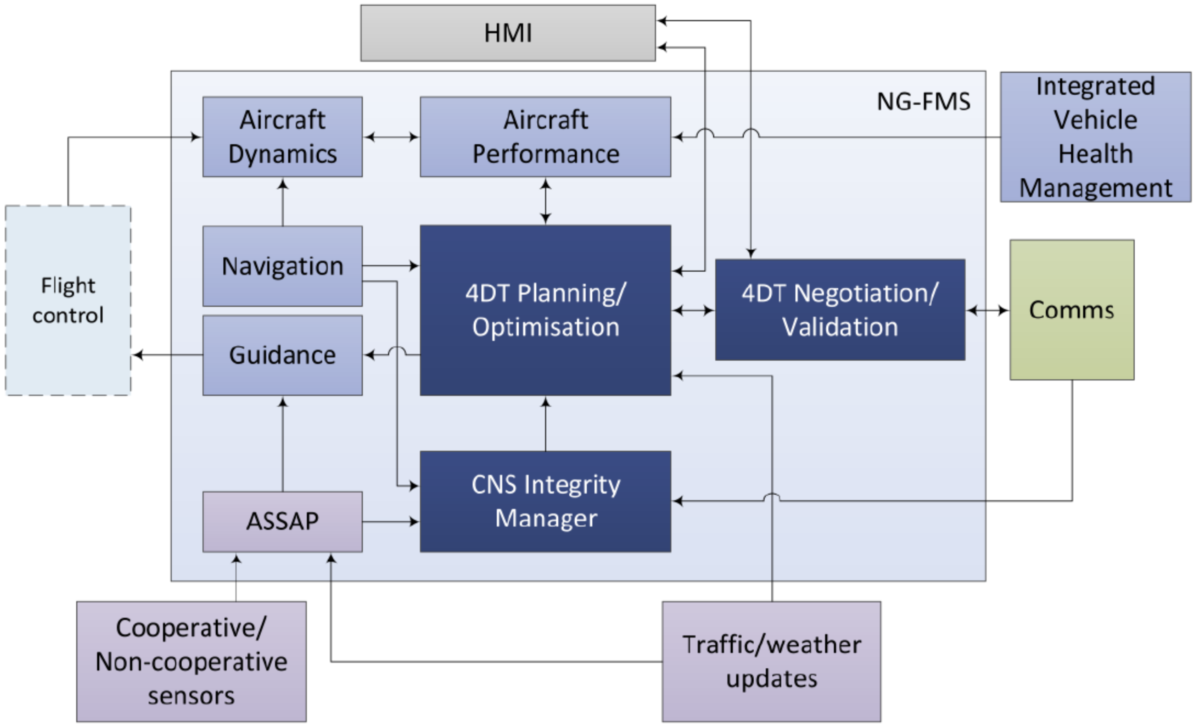

Figure 23. NG-FMS Architecture [16].

8.4. Cognitive HMI

"The cognitive HMI (CHMI) is a crucial component of the VPA system, providing the necessary reductions in workload as well as incapacitation-detecting capabilities that will support the case for SPO certification. Section 5.4.2 of the DOD's Unmanned Systems Integrated Roadmap has identified adaptive interfaces as a key future development for autonomous systems [293]. The CHMI assists the pilot with several intelligent functions such as information management, adaptive alerting, situation assessment as well as task allocation. The proposed design of the CHMI in the VPA system is based on the guidelines specified in FAR AC 25.1302-1 with regards to the human factors engineering and system redundancy for safe and effective operations." [16]. In addition, EASA AMC 25.1302 provides guidance for the "design and approval of installed equipment" as well as "recommendations for the design and evaluation of controls, displays, system behaviour, and system integration", and "design guidance for error management."

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9. Conclusion

This deliverable set the starting point of the project.

It defined the context in which the HARVIS roadmap will be developed, specifying the steps needed, in terms of technology development, interaction design and training, to develop such an assistant.

It will also be used to build specific use cases, to make specific examples of an AI based virtual assistant able to enable and support Single Pilot Operations.

The next step is now to better define the tasks that the pilots will have to perform in the future context identified in this document, and understand which ones need to be (and can be) supported by a digital assistant. This will be done in D2.1 Analysis of Potential Cognitive Computing Aided Tasks.

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Appendix A Levels of Automation

Levels of Automation Taxonomy (LOAT).

From INFORMATION to ACTION

INCREASING AUTOMATION

A INFORMATION ACQUISITION		B INFORMATION ANALYSIS		C DECISION AND ACTION SELECTION		D ACTION IMPLEMENTATION	
Human Information Acquisition		**Human Information Analysis**		**Human Decision Making**		**Human Action Execution**	
The **human acquires** relevant information on the process s/he is following.	**A0 Manual** Without using any tool	The **human compares**, and analyses different information items regarding the status of the process s/he is following	**B0 Manual** Without using any tool or support external to her/his working memory.	The **human generates** decision options, selects the appropriate ones and decides all actions to be performed.	**C0 Manual** Without using any tool.	The **human executes** and controls all actions.	**D0 Manual** Without using any tool.
	A1 Artefact-Supported With the support of low-tech non-digital artefacts		**B1 Artefact Supported** With the support of low-tech non-digital artefacts.		**C1 Artefact Supported** With the support of low-tech non-digital artefacts.		**D1 Artefact Supported** With the support of mechanical non-software based tools.
Automation Support to Information Acquisition		**Automation Support to Information Analysis**		**Automation Support to Decision Making**		**Automation Support to Action Implementation**	
The **system supports** the user in acquiring information on the process s/he is following.	**A2 Low Level** Filtering and/or highlighting of the most relevant information are up to the user.	The **system supports** the user in comparing and analysing different information items regarding the status of the process being followed.	**B2 Low Level** The support is offered only on user request.	The **system proposes** one or more decision alternatives to the user.	**C2 Open** The user can select one of the alternatives proposed by the system or her/his own one.	The **system assists** the user in performing actions.	**D2 Low Level** By executing part of an action and/or by providing guidance and feedback during its execution. Each action is executed based on user initiative and the user keeps full control on the execution.

	A3 Medium Level The system integrates data coming from different sources and filters and/or highlight the most relevant information items, based on user's settings		**B3 Medium Level** The support is offered only on user request. The system triggers visual and/or aural alerts if the analysis produces results requiring attention by the user.		**C3 Rigid** The user can only select one of the alternatives or ask the system to generate new options.		**D3 Medium Level** By executing a sequence of actions after activation by the user. The user maintains full control of the sequence and can modify or interrupt it at any time
The **system supports** the user in acquiring information on the process s/he is following.	**A4 High Level** It integrates data coming from different sources and filters and/or highlights the information items relevant for the user. The criteria for integrating, filtering and highlighting the info are predefined at design level and visible to the user	The **system supports** the user in comparing and analysing different information items regarding the status of the process being followed.	**B4 High Level** The support is offered automatically, based on parameters adjustable by the user. The system triggers visual and/or aural alerts if the analysis produces results requiring attention by the user.			The **system assists** the user in performing actions.	**D4 High Level** By executing a sequence of actions after activation by the user. The user can monitor all the sequence and can interrupt it during its execution.
	A5 Full It integrates data coming from different sources and filters		**B5 Full** The support is offered automatically, based on parameters predefined at design level. The system				

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	and/or highlights the information items relevant for the user. The criteria for integrating, filtering and highlighting the info are predefined at design level but not visible to the user		triggers visual and/or aural alerts if the analysis produces results requiring attention by the user.				
				Automatic Decision Making		**Automatic Action Implementation**	
					C4 Low Level The human is informed of its decision		**D5 Low Level** The human can monitor all the sequence and can modify or interrupt it during its execution
				The **system decides** autonomously the actions to be performed.	**C5 Medium Level** The human is informed of its decision only on request *Always connected to Action Implementation* ***D5-D8***	The **system initiates** and **executes** automatically a sequence of actions.	**D6 Medium Level** The human can monitor all the sequence and can interrupt it during its execution
					C6 High Level The human is not informed of its decision *Always connected to Action Implementation* ***D5-D8***		**D7 High Level** The human can monitor part of the sequence and has limited opportunities to interrupt it.
							D8 Full The human cannot monitor nor

				interrupt it until the sequence is not terminated.

Figure 24: Extended version of the LOAT

More information available here: https://dblue.it/projects/project-levels-automation-taxonomy/

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