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Ph.D. THESIS

NEUROPHYSIOLOGICAL CORRELATES OF PSYCHOLOGICAL ATTITUDES OF AIR TRAFFIC CONTROLLERS DURING THEIR WORK

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To Marco and my family

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SUMMARY

1. LIST OF ABBREVIATIONS

AAS	ANTERIOR ATTENTIONAL SYSTEM
ACC	ANTERIOR CINGULATE CORTEX
ANOVA	ANALYSIS OF VARIANCE
asSWLDA	AUTOMATIC STOP STEPWISE LINEAR DISCRIMINANT ANALYSIS
ATCOs	AIR TRAFFIC CONTROLLERS
ATM	AIR TRAFFIC MANAGEMENT
AUC	AREA UNDER CURVE
CI	CONFIDENCE INTERVAL
EEG	ELECTROENCEPHALOGRAPHY
EKG	ELECTROCARDIOGRAPHY
ENAC	ÉCOLE NATIONALE DE L’AVIATION CIVILE
ENAV	ENTE NAZIONALE DI ASSISTENZA AL VOLO
EOG	ELECTROOCULOGRAPHY
EPs	EVOKED POTENTIALS
ERD	EVENT-RELATED DESYNCHRONIZATION
ERS	EVENT-RELATED SYNCHRONIZATION
FEF	FRONTAL EYE FIELDS
FFT	FAST FOURIER TRANSFORM
FPL	FLIGHT PLAN LEVEL
HF	HUMAN FACTORS

IAF	INDIVIDUAL ALPHA FREQUENCY
IFG	INFERIOR FRONTAL GYRUS
IPL	INFERIOR PARIETAL LOBULE
IPS	INTRAPARIETAL SULCUS
KS	KNOWLEDGE SYSTEM
LTM	LONG-TERM MEMORY
MFG	MIDDLE FRONTAL GYRUS
mPFC	MEDIAL PREFRONTAL CORTEX
NINA	NEUROMETRICS INDICATORS FOR AIR TRAFFIC MANAGEMENT
OC	CLOSED EYES
PAS	POSTERIOR ATTENTIONAL SYSTEM
PSD	POWER SPECTRAL DENSITY
REF	REFERENCE
ROC	RECEIVER OPERATING CHARACTERISTIC
SME	SMALL- AND MEDIUM- SIZED ENTERPRISES
SME	SUBJECT-MATTER EXPERT
SPL	SUPERIOR PARIETAL LOBULE
SRK	SKILL – RULE – KNOWLEDGE
STG	SUPERIOR TEMPORAL GYRUS
TCAS	TRAFFIC COLLISION AVOIDANCE SYSTEM
TPJ	TEMPOROPARIETAL JUNCTION
TRACONs	TERMINAL RADAR APPROACH CONTROL CENTRES

UFO	UNIDENTIFIED FLYING OBJECT
VFC	VENTRAL FRONTAL CORTEX
vmPFC	VENTROMEDIAL PREFRONTAL CORTEX

2. INTRODUCTION

The research proposed in this thesis is part of a European project called NINA (Neurometrics Indicators for Air Traffic Management) funded by Sesar Joint Undertaking [1], and it involves the participation of Sapienza University of Rome, École Nationale de l’Aviation Civile (ENAC), and Deep Blue srl (Human Factor and Safety Consultant Company).

The main goal of the project is to elaborate neurophysiological measurements for real-time assessment and monitoring of the cognitive state in particular professional categories, such as Air Traffic Controllers (ATCOs). The evaluation is performed by using a combination of techniques such as Electroencephalography (EEG), Electrocardiography (EKG) and Electrooculography (EOG), during simulated and realistic working conditions.

In the area of ATCOs, the Skill, Rule and Knowledge (S-R-K) taxonomy was developed by Rasmussen [2] to describe the human performance under various circumstances and to integrate a variety of research results coming from human cognition studies (attention, memory, problem solving, decision-making, etc.) under a common framework. It provides a description of human cognition that is functional to the understanding and prediction of behaviour: it specifically deals with how people control their activity and behave in interaction with complex systems. Therefore, by considering the aspect of the cognitive processes in the framework of such taxonomy, it is possible to contextualise them in the work practices.

Since to our knowledge there are no corresponding studies in the existing literature, another challenging objective of the project is to develop the SRK concept from a neurophysiological point of view. The focus of the proposed thesis is thus to verify the existence of identifiable neurophysiological features associated to the three levels of cognitive control of behaviour

(Skill, Rule and Knowledge), in Air Traffic Management (ATM) context, by using a neurometric able to identify the behaviours of the original taxonomy from a different perspective.

To map the neurophysiology of the SRK framework in ATM domain, and to use this methodology, could represent a promising step forward into the analysis of human behaviour, and furthermore, to develop new Human Factors tools able to discriminate the level of operators' expertise during ecological tasks.

In detail, the first part of this work illustrates a brief description of the brain and the Electroencephalographic technique, then an introduction of the NINA project and the literature related to the S-R-K levels of cognitive control are presented.

The second section is focused on some additional brain features' literature and on the experimental phase where several steps were performed as follows:

a) the three categories of behaviours were associated with specific cognitive functions (e.g. attention, memory, decision making etc.) already investigated in literature with EEG measurements;
b) a link between S-R-K behaviours and expected EEG frequency bands configurations were hypothesized;
c) specific events were designed to trigger S, R and K behaviours and integrated into realistic ATM simulations;
d) finally, the machine-learning algorithm automatic stop StepWise Linear Discriminant Analysis (asSWLDA) was trained to differentiate the three levels of cognitive control of

behaviour by using brain features extracted from the EEG rhythms of different brain areas.

Several professional ATCOs from the École Nationale de l'Aviation Civile (ENAC) of Toulouse (France) were involved in the study and the results showed that the classification algorithm was able to discriminate with high reliability the three levels of cognitive control of behaviour during simulated air-traffic scenarios in an ecological ATM environment.

The work proposed in this thesis was performed by the Sapienza team which I am part together with Biomedical Engineers, and performed in collaboration with Air Traffic Controllers and Human Factors experts working in the same context of research.

Please note that the terms levels of cognitive control of behaviour, levels of performance and levels of behaviour or expertise, are used as synonyms in this work.

3. PART I

3.1 THE BRAIN AND THE ELECTROENCEPHALOGRAPHY

Before describing the neurophysiological measurements, it is important to have an overview on the brain, its lobes and their functions, and on how the electrical activity of the brain is detected.

The human brain is the most important organ of the central nervous system (CNS) and is characterised by two hemispheres: the right and the left. The two hemispheres communicate each other across the corpus callosum, a bundle of neural fibers. The surface part of the brain is called cerebral cortex: it appears full of fissurations and convolutions, and is composed of gray matter, consisting mainly of cell bodies. The cerebral cortex plays a key role in memory, attention, perception, awareness, thought, language, and consciousness.

The brain can also be divided into four areas called lobes: frontal, parietal, temporal and occipital (Figure 1). Each lobe has specific functions:

1. The **frontal lobe** is responsible for initiating, coordinating and planning motor movements and monitoring the executive behavior. It is involved in higher cognitive skills (such as problem solving, decision-making, thinking, planning, and organizing, judgment), and many aspects of personality and emotional components (impulse control, social and sexual behavior), Furthermore, it assists working memory and language production.
2. The **parietal lobe** receives projections from all the other lobes and can be considered the “association cortex” as plays an important role in integrating visual, auditory, and somatosensory information for guiding the behavior (e.g. grasping and manipulation of the objects). Its functions also include the spoken and written language, the

processing information related to the sense of touch. It is also essential in cognitive functions such as working memory, numerical processing, and attention; in particular, it is involved with visuo-spatial information processing and attentional orientation.

3. The **temporal lobe** is involved in the retention of visual memories, the processing of sensory inputs (e.g. auditory and visual), the language comprehension and verbal memory, the storing of new memories, the emotion and deriving meaning. Furthermore, it includes the hippocampus and plays a key role in the formation and encoding of explicit long-term memory, and in learned emotional responses modulated by the amygdala.
4. The **occipital lobe** is the visual processing center of the brain that includes different areas of the visual cortex. One part of the visual cortex, the primary visual cortex (striate cortex or V1), is a region that receives input from the retina of the eye. This is where the mind interprets color and other important aspects of vision. There are also extrastriate regions (V2, V3, V4, and V5) specialized for different visual tasks, such as visuo-spatial processing, color discrimination and motion perception. Each functional visual area of the occipital lobe contains a full map of the visual world, although there are no anatomical markers distinguishing these areas, except for the striate cortex.

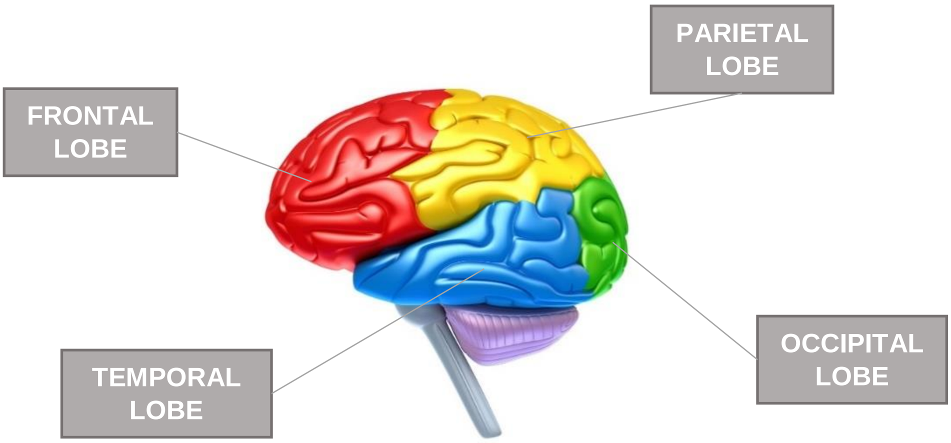

Figure 1 – The brain lobes

The electrical activity of the brain lobes is produced by billions of neurons, electrically polarized, that constantly exchange ions with the extracellular milieu across their membranes. When the neuron is not transmitting a signal, it is in a *resting state*: the inside of the cell has a negative charge, while the outside of the cell has a positive charge. The membrane is called *polarized* because negative and positive charges exist on opposite sides.

Almost every neuron has a single axon, specialized for the conduction of a specific type of electrical impulse, called *action potential* (Figure 2). The action potential consists in a sudden, transient depolarization (change in the voltage) of the membrane, followed by a repolarization to the resting potential of about −70 mV. The action potential moves rapidly, up to 100 meters per second, and, at its peak of propagation, the membrane potential can be as much as +50 mV (inside positive), a net change of ≈110 mV.

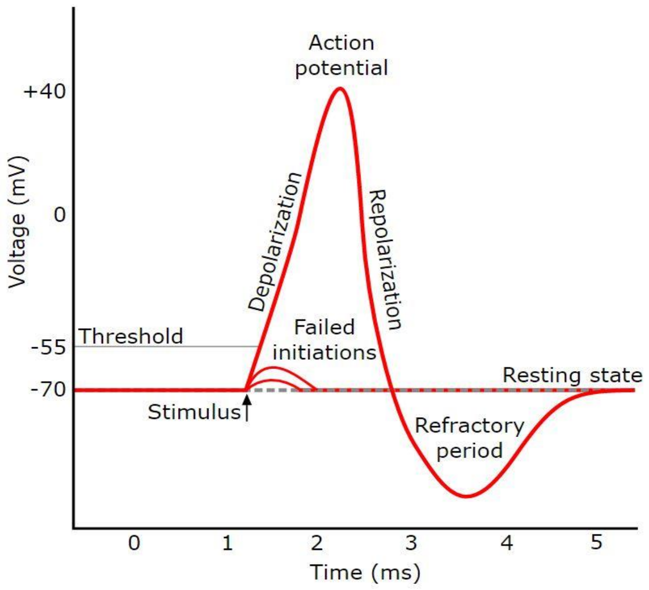

Figure 2 – Electrophysiological recording of an action potential

The electrical signals deriving from the activity of the brain can be detected with electrodes along the scalp through the Electroencephalography (EEG), a technique able to measure the voltage fluctuations resulting from ionic current flows within the neurons of the brain [3]. The largest contribution to genesis of the EEG is due to the post-synaptic potential, both excitatory and inhibitory, not to the action potential.

The EEG activity reflects the summation of the synchronous firing of millions of neurons (pyramidal cells mainly). Its oscillatory activity is characterised by five different frequency bands (Figure 3) which can be associated with different states of brain functioning (e.g. waking and the various sleep stages, cognitive functions, etc.):

a) **Delta** (0-4 Hz), its activity is characterised by high amplitude and low frequency. It is usually associated with the slow-waves sleep in the psychophysiology of sleep. It is suggested that this frequency band represents the onset of deep sleep phases in healthy adults [4].

b) **Theta** (4-7 Hz), its genesis is associated with the hippocampus [5] as well as the neocortex [6]. It is thought to be linked to deep relaxation or meditation [7], and it has been observed during the transition between wake and sleep [8]. However, theta rhythms are suggested to be influential for learning and memory functions [9], encoding and retrieval [10] which involve high concentration [8]. It is also suggested that theta oscillations are associated with the attentional control mechanism in the anterior cingulated cortex [7], [11]. Theta frequency band is often shown to increase with high cognitive task demand [12], [13].

c) **Alpha** (8-12 Hz), its activity is found in the visual cortex (occipital lobe) during periods of relaxation or cortical idling (eyes closed but awake). In the continuous EEG, the alpha band is characterised by high amplitude and regular oscillations, in particular over parietal and occipital areas. Although high alpha activity is assumed to reflect a state of relaxation or idling, when an operator assigns more effort to a task, different regions of the cortex may be recruited in the transient function network leading to passive oscillation of the local alpha generators, in synchrony with a reduction in alpha activity [11]. Recent results have suggested that alpha is also involved in the inhibition of task irrelevant areas to enhance signal-to-noise ratio, and in the auditory attention processes [14], [8]. Besides, research on alpha ERS/ERD (event-related synchronization/desynchronization) have revealed that different patterns of alpha (de-)synchronization can be observed when the broad alpha frequency range (approximately in the range between 8 and 12 Hz) is divided into several alpha sub-bands [15]. Specifically, lower alpha ERD (~8–10 Hz) has been found as being more likely to reflect general task demands such as attentional processes (basic alertness, vigilance or arousal). ERD in the upper alpha band (~10–12 Hz) has been observed as being more sensitive to specific task requirements for example, semantic memory processes [16]-[18].

d) **Beta** (12-30 Hz), is predominant in wakefulness state, especially in frontal and central areas of the brain. High power in beta band is associated with the increased arousal and activity. Dooley [19] pointed out that beta wave represents cognitive consciousness and active, busy, or anxious thinking. Furthermore, it has been revealed to reflect visual concentration and the orienting of attention [20]. This frequency band can be further divided into: low beta wave (12.5-15 Hz), middle beta wave (15-18 Hz), high beta wave (>18 Hz). Low waves seem to be associated with inhibition of phasic movements during sleep and high waves with dopaminergic system [8].

e) **Gamma** (30-100+ Hz), is the fastest activity in EEG and is thought to be not frequent during waking states of consciousness [19]. Recent studies have revealed that it is linked with many cognitive functions such as attention, learning, and memory [21].

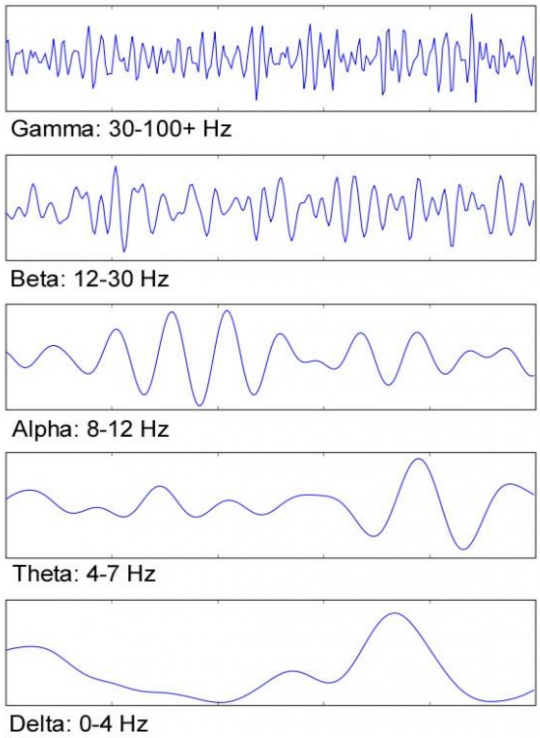

Figure 3 – EEG frequency bands

The EEG is one of the most used and accepted neurophysiological technique for the assessment of the cognitive state during the performance of a task and two basic approaches are commonly used for the EEG analysis:

1. The **analysis of Evoked Potentials (EPs)**, consisting in a response induced by the presentation of an external stimulus that can be isolated and analysed from the electroencephalographic spontaneous activity;
2. The **Power Spectral Density (PSD)** or power spectral analysis of the EEG rhythms or is one of the standard methods used for quantification of the EEG that shows the strength of the variations (energy) as a function of frequency. In other words, it shows at which frequencies variations are strong and at which frequencies variations are

weak. PSD is a very useful tool to understand frequencies and amplitudes of oscillatory signals in a time series data.

The two methods have been applied in various experimental researches into human cognitive activities anyway, in this thesis, the focus is set on the PSD analysis of the EEG rhythms.

3.2 THE NINA PROJECT: NEUROMETRICS INDICATORS FOR AIR TRAFFIC MANAGEMENT

This section starts with a brief description of the Air Traffic Management (ATM) domain, then it paves the way to the experimental phase, presented further on in this thesis, with a picture of the NINA project objectives, phases and activities which helps to have a better comprehension on the attempt to achieve a possible integration between the SRK framework and neurophysiological variables.

Further information on the project, can be found at the following link http://www.nina-wpe.eu/.

Air Traffic Management (ATM) and Air Traffic Control (ATC)

The **Air Traffic Management (ATM)** is an activity composed of complex processes and control systems. It includes all the procedures, technology and human resources which make sure that:

- The aircrafts are guided safely through the sky and on the ground;
- The airspace is managed to accommodate the changing needs of air traffic over time.

Any aircraft using Air Traffic Control, from a business aeroplane to an airliner, files a flight plan and sends it to a central repository. All flight plans for flight into, out of and around a controlled sector are analysed and computed.

For safety reasons, Air Traffic Controllers cannot handle too many flights at once, so the number of flights they control at any one time is limited. Sophisticated computers used by Air Traffic Flow Management calculate exactly where an aircraft will be at any given moment and check that the controllers in that airspace can safely cope with the flight. If they cannot, the aircraft must wait on the ground until it is safe to take off.

On the other hand, the **Air Traffic Control (ATC)** is a service provided by air traffic controllers who manage the process by which aircraft are safely separated through the controlled airspace and on the ground where they land and take off again.

The primary purpose of ATC worldwide is to prevent collisions, organize and expedite the flow of air traffic, and provide information and other support for pilots. To prevent collisions, ATC enforces traffic separation rules, which ensure each aircraft maintains a minimum amount of empty space around it. Many aircraft also have collision avoidance systems, which provide additional safety by warning pilots when other aircraft get too close.

Europe has many large Air Traffic Control Centres which guide aircraft to and from terminal areas around airports [22], [23].

The Air Traffic Controllers (ATCOs) are operators trained to coordinate and maintain safe, orderly, and rapid the traffic flow in specific controlled sectors of the ground and sky. The position of ATCO requires highly specialized knowledge, skills, and abilities. Typically, they do the following tasks:

- Coordinate the arrival and departure of airplanes and issue landing and take-off instructions to pilots
- Monitor and direct the movement of aircraft on the ground and in the air, using radar equipment, computers, or visual references
- Authorize flight path changes
- Control all ground traffic at airports, including baggage vehicles and airport workers

- Manage communications by transferring control of departing flights to traffic control centres and accepting control of arriving flights
- Provide information to pilots, such as weather updates, runway closures, and other critical information
- Alert airport response staff, in the event of an aircraft emergency

ATCOs' primary concern is safety, but they also must direct aircraft efficiently to minimize delays. They usually manage multiple aircraft at the same time and must make quick decisions to ensure the safety of the aircraft. For example, a controller might direct one aircraft on its landing approach, while providing another aircraft with weather information.
There are different types of air traffic controllers:

1. *Tower controllers,* direct the movement of vehicles on runways and taxiways. They check flight plans, give pilots clearance for take-off or landing, and direct the movement of aircraft and other traffic on the runways and other parts of the airport. Most work from control towers, as they generally must be able to see the traffic they control.
2. *Approach and departure controllers,* ensure that aircraft traveling within an airport's airspace maintain minimum separation for safety. They give clearances to enter controlled airspace and hand off control of aircraft to en route controllers. They use radar equipment to monitor flight paths and work in buildings known as Terminal Radar Approach Control Centres (TRACONs). They also provide information to pilots, such as weather conditions and other critical notices.

3. *En route controllers,* monitor aircraft once they leave an airport's airspace. They work at air route traffic control centres located throughout the country.

Each centre is assigned an airspace based on the geography and altitude of the area in which it is located. As an airplane approaches and flies through a centre's airspace, en route controllers guide the airplane along its route. They may adjust the flight path of aircraft for safety and collision avoidance. As an airplane goes along its route, en route controllers hand the plane off to the next centre, approach control, or tower along the path, as needed. En route controllers pay special attention to aircraft as they descend and get closer to the busier airspace around an airport. En route controllers turn the aircraft over to the airport's approach controllers when the aircraft is about 50 miles from the airport.

Some air traffic controllers work at the Air Traffic Control Systems Command Centre. These controllers monitor traffic patterns within the entire national airspace that could create bottlenecks in the system. When they find a bottleneck, they provide instructions to other controllers that help to prevent traffic jams. Their objective is to keep traffic levels manageable for the airport and for en route controllers.

The NINA Project

NINA (Neurometrics indicators for Air Traffic Management) is a project co-funded in the SESAR WPE framework that brings together three highly qualified partners with complementary competencies coming from academia, research institution and small- and medium-sized enterprises (SME): Sapienza University of Rome, École Nationale de l'Aviation Civile (ENAC) and Deep Blue srl (Human Factor and Safety Consultant Company). The NINA project intends to take advantage of these results and innovations to monitor the cognitive state of ATM operators and identify appropriate actions to support their activity, using a combination of neurometrics and other neurophysiological measures. The measurements, recorded through the Electroencephalography (EEG), Electrooculography (EOG), and Electrocardiography (EKG), are collected through a non-invasive equipment with sensors that in an industrial version of the device could be substituted with a cap connected through a wi-fi link.

By collecting the data showing the “internal” attentive and cognitive state of the operator (i.e. information regarding the vigilance state, the level of cognitive workload and the type of cognitive activity he is engaged in), NINA shapes the activity of the operators. The adoption of Ecological Interfaces Design, to create interfaces that adapt to the mental state of the operator, can lessen mental workload, particularly when dealing with unforeseen and unfamiliar events under increased psychological pressure.

Therefore, the objectives of the project are:

1. To monitor the level of cognitive workload of ATM operators in a realistic ATC context, through a combination of neurometrics and neurophysiological measures, characterising the relation between the measured variables and the work performances.
2. To verify the existence of identifiable neurophysiological conditions associated to the levels of cognitive control of behaviour (Skill, Rule, and Knowledge) defined by well-established cognitive models, using a combination of neurophysiological measures.
3. To identify, prototype and evaluate the main elements of a simple adaptive interface in which adaptation is triggered by the described measures, and based on the key principles of an ecological interface (at the Skills, Rules and Knowledge levels of the cognitive control).

4. To validate the above results in realistic conditions through real ATM simulation facilities.

NINA Project: phases and activities

It is possible to divide the NINA project into two main parts: the first one where it was demonstrated the feasibility of measuring and monitoring the ATCO's mental state by using a combination of neurophysiological signals throughout the Baseline measurement, the Calibration and the First Validation phases, and the second one characterised by the activities of the Second Validation.

Figure 4 shows the synthesis of the activities conducted in both the first and the second part.

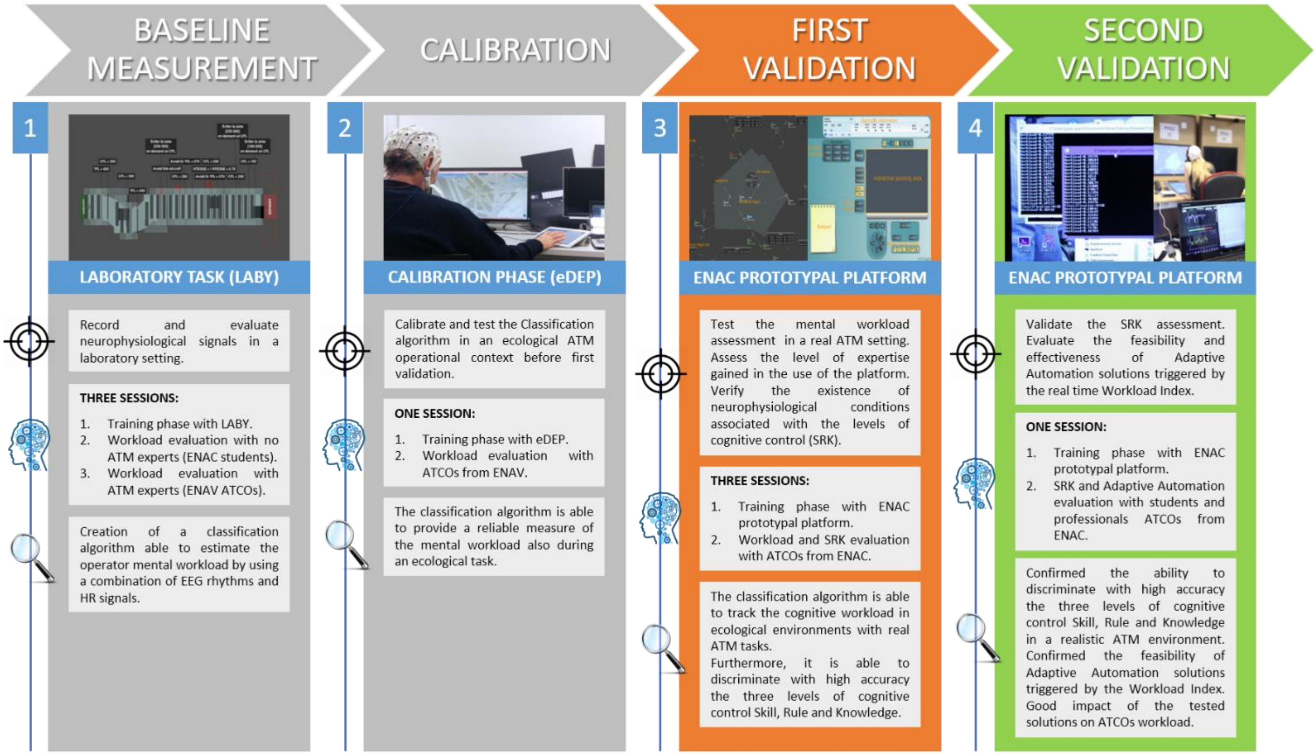

Figure 4 – NINA Project phases and activities

The Baseline measurement, the Calibration of the classification algorithm and the First Validation activity, were characterised by different levels of reliability (from the laboratory setting to real ATM simulation facilities, with realistic ATM tasks).

The main aim of this activity was to develop, tune, and validate the classification algorithm, namely an objective psychophysiological measurement able to provide a real-time evaluation of the level of ATCOs' mental state with high accuracy, specifically, the level of mental workload, the level of training, and the levels of cognitive control of behaviour (SRK). After the First Validation activity, several actions were performed for the identification of different adaptive solutions implemented and tested during the Second Validation session. The goal of these preliminary actions (workshop and focus group with Operational, Human Factors and Neurophysiological Experts) was to define, identify and collect materials to set up the next stage of the project. The results obtained during the preliminary actions, led to the identification of realistic ATM scenarios and adaptive solutions for the Second Validation.

Validation activities

As mentioned before, the main results achieved during the First Validation activity was further analysed and extended through the Second Validation activity. This section describes the results of the approach used.

The First Validation intended to validate the ability of the neurophysiological measures in monitoring the level of operators' workload and training in real ATM settings, and to assess how these neurometrics could provide information about a specific Human Factors concept like the level of cognitive control (SRK) from professional ATCOs engaged in an ecological ATM task. The results from the First Validation activity demonstrated the reliability of the classification algorithm (EEG algorithm) to evaluate the operators' mental workload and level of training using neurophysiological measures, and to differentiate with a high accuracy the actual operators' cognitive control (SRK levels).

The Second Validation intended to confirm the previous results connected to the evaluation of levels of cognitive control of behaviour (SRK) using EEG signals and use the real-time information coming from the classification algorithm to trigger simple adaptive automation solutions on the base of the ATCO's current mental workload.

Figure 5 provides a summary of this concept and shows how the results gained through the First Validation led up to the Second Validation activity.

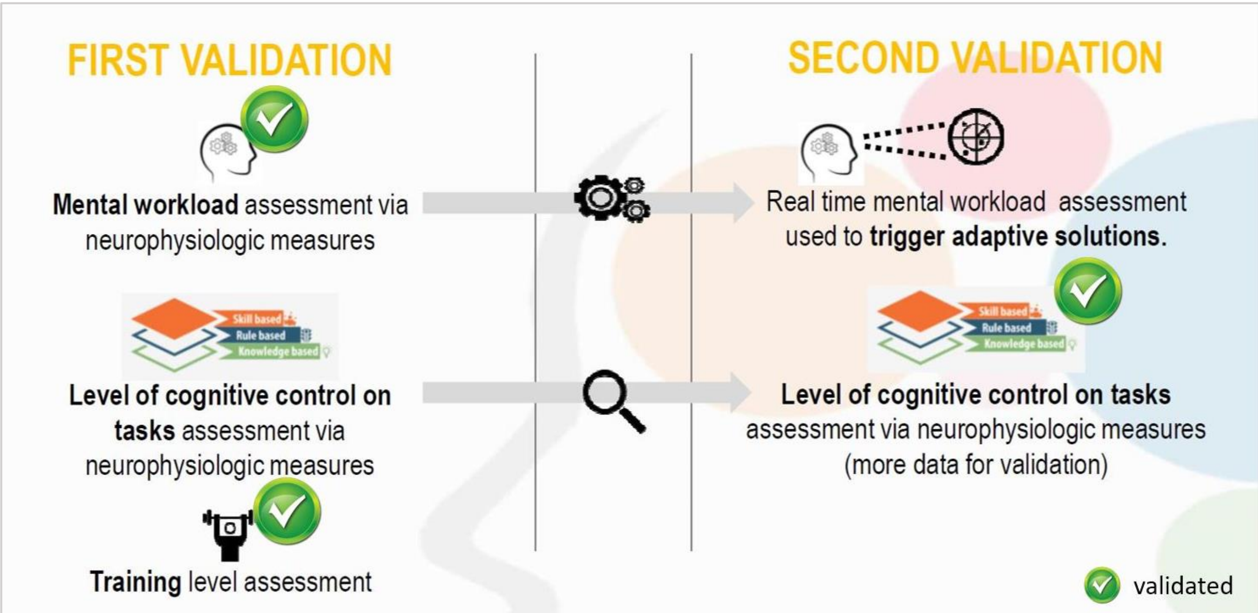

Figure 5 – Link between First and Second Validation

Indeed, the results gained during First Validation activity demonstrated the reliability of the classification algorithm to track the level of cognitive workload as well as the level of training and proficiency achieved by controllers in real ATM tasks. The results related to the feasibility to assess the level of cognitive performance (SRK), demonstrated also that the classification algorithm could significantly differentiate the current controllers' levels of performance (SRK), even if this concept was further investigated during the Second Validation with a wider sample of subjects.

Similarly, the results gained through the Second Validation allowed to confirm the previous results on the SRK framework, and thus to validate the ability of the classification algorithm to discriminate the S, R and K conditions with a high level of accuracy.

The results demonstrated also the feasibility to trigger new adaptive solutions starting from the real-time information coming from the classification algorithm about the current workload of the controllers. Furthermore, was possible to evaluate the impact of these adaptive solutions on controllers' workload in realistic ATM environments.

3.3 THE STATE OF COGNITIVE CONTROL OF BEHAVIOUR: THE SKILL, RULE AND KNOWLEDGE FRAMEWORK

The Skills, Rules, Knowledge (SRK) framework or SRK taxonomy is one of the several models used for representing the cognitive human behaviour especially when the operator has to cope with complex man-made systems in routine task environments and during unfamiliar conditions. Specifically, the framework was developed by Rasmussen [1] and refers to *"the degree of conscious control exercised by the individual over his or her activities, depending on the degree of familiarity with the task and the environment"*; it was developed to help designers combine information requirements for a system and aspects of human cognition.

Before describing the model, it is worth noting that humans are not simply input-output devices but goal-oriented individuals who actively select their goals and relevant information; furthermore, the efficiency of humans in coping with complexity is widely due to the availability of a large repertoire of different mental representations of the environment from which rules to control behavior can be generated *ad hoc*. The interaction with an environment depends upon the existence of a set of invariate constraints in the relationships among events in the environment, human actions and their effects. The implications are that intentional behavior must be based on an internal representation of these constraints characterizing the different categories of human behavior. According to different ways of representing the constraints in the behavior, three levels of performance can be identified: skill-, rule-, and knowledge-based behaviour.

The **Skill-based Behaviour** represents sensory-motor performance during acts or activities which, following a formed intention, take place without conscious control or cognitive effort as smooth, automated, and highly integrated patterns of behavior. In fact, once the skills or patterns are acquired, the automaticity allows operators to free up cognitive resources, which can then be used for higher cognitive functions like problem solving [24].

Only occasionally the skilled performance is based on simple feedback control, where motor output is a response to an error signal representing the difference between the actual state and the intended state in the environment. In most skilled sensory-motor tasks, the body acts as a multivariable continuous control system, synchronizing movements as a function of the environment. At this level, the performance is based on feedforward control and depends upon a very flexible and efficient dynamic internal world model.

Typically, skill-based performance rolls along without conscious attention or control: the entire performance is smooth and integrated, and the senses are only directed towards the aspects of the environment needed subconsciously to update and orient the internal map.

In some cases, where the performance is a continuous integrated dynamic whole such as bicycle riding or musical performance, the higher-level control may take the form of conscious intentions to adjust the skill in general terms, for example *"Be careful now, the road is slippery"* or *"Watch out, now comes a difficult passage"*. In other cases, the performance is a sequence of rather isolated skilled routines which are sequences of a conscious executive program.

In general, human activities can be considered as a sequence of such skilled acts or activities composed for the actual occasion. The flexibility of skilled performance is due to the ability to compose, from a large repertoire of automated subroutines, the sets suited for specific purposes [25].

The **Rule-based Behaviour** is the procedural behaviour, composed of a sequence of subroutines in a familiar work situation, typically controlled by a stored rule or procedure, which may be acquired empirically during previous experiences, communicated as instructions from supervisors and former operators' know-how, or prepared on occasion by conscious problem solving and planning. At this level, the performance is goal-oriented but structured by feedforward control through stored rules. Very often, the goal is not even explicitly formulated, but it is implicitly found from previous successful experiences. In fact, the rule-based level, requires some degrees of attention to assess and recognize a familiar situation that leads to the application of specific procedures. The recognition of a familiar event may activate a set of rules included into the library of rules *“if X, then Y”* that were successful in previous situations.

Feedback correction during performance requires functional understanding and analysis of the current response of the environment, which may be considered as an independent concurrent activity at the higher level (knowledge-based).

The boundary between skill-based and rule-based performance is not quite distinct, and much depends on the level of training and on the attention of the person. In general, the skill-based performance rolls along without the operator's conscious attention, and he/she will be unable to describe how he/she controls and on what information bases the performance. The higher-level rule-based coordination is generally based on explicit know-how, and the rules used can be reported by the person.

The **Knowledge-based Behaviour** is characterised by unfamiliar or unexpected situations when the operator has to face with an environment for which no know-how or proven rules are available or inadequate from previous experiences; in this case, the control of performance must move to a higher conceptual level, in which performance is goal-controlled and knowledge-based. Typically, this level of performance is considered as a complex process of collection, integration and analysis of different information from the environment that, once interpreted, result in the comprehension of the current situation, and in the planning and execution of a new appropriate plan of actions; the attempts to reach the goal are not performed in reality, but internally as a problem-solving exercise, i.e. the successful sequence is selected from experiments with an internal representation or model of the properties and behavior of the environment. Then, a new rule and useful plan is developed among the different plans or combination of actions and rules considered, and their effect tested against the goal either *physically*, by trial and error, or *conceptually*, by means of “thought experiments”. An example could be when the pedals of your bike stop working properly. You do not know what is happening; your bike has never had any problem. While you continue to ride, you try to look at the pedals and the gears trying to imagine what is the problem, but you are not able to identify any apparent one. Finally, you stop the bike in order to try to understand the issue and find a solution. From a skill-based and rule-based behaviour you have to shift to a knowledge-based behaviour.

At this level of functional reasoning, the internal structure of the system (of the world) is explicitly represented by a “mental model" which may take several different forms. The control on the performance is thus principally based on feedback, on information that emerges from the world. Unlike skill-based behaviour and rule-based behaviour, where the check comes from feedforward, the knowledge-based behaviour is on active information seeking and on the accurate check of the intermediate action results.

Moreover, something must be remarked about the information deriving from the environment which is basically different in the various categories. This is the case of unfamiliar situations, when same information could be perceived in many ways depending on the operator's expertise level. As described by Reason [26], each level of behaviour is related to specific types of performance and error: e.g. as the skill level is characterised by a low level of control, the response is rapid, effortless, flexible and resistant to changes but it is also related to slips and lapses errors. While performing at the rule-based level, it is possible to quickly and effectively face familiar and anticipate unfamiliar events, but rule-based mistakes can happen, such as the misapplication of right rules or the application of wrong rules. Finally, the knowledge-based behaviour leads to the resolution of new problems, new rules and, in general, to innovation and creativity even though this behaviour is slow, cognitively demanding and very prone to error.

The three levels of cognitive control of behaviour are concerned as a dynamic system that generally works in parallel and are integrated, where the control of behavior continuously shifts from a level to another one. Such a structure allows to react quickly to environmental changes, to deal with ambiguous situations, to solve familiar or unfamiliar problems and to set new problems in an efficient and flexible way.

When expertise evolves, cognitive control shifts, for example when a subject is learning to drive, his/her attention and cognitive resources are located to the set of actions of "driving a car". These rule-based behavior, with practice, requires less and less attention and control until it becomes automated, shifting to the skill-based level. Another example is in learning to use the T9 keyboard system on the mobile phone. The first time is knowledge-based to diagnose the way for using T9 and produce a rule. When the procedure to select letters and words is known, the control shifts to the rule-based behavior for applying the rules learned. Finally, after practice, the procedure may turn automated, therefore skill-based.

3.4 TOWARDS A POSSIBLE CORRELATION BETWEEN THE SRK FRAMEWORK AND NEUROPHYSIOLOGICAL FEATURES

This section reviews interesting issues about the neuroanatomical and functional models which may be related to the level of attentional control, for a possible integration between the SRK framework and neurophysiological variables.

Models of attentional control

One of the first models of attentional control was proposed by Posner and Petersen [27]. It consists of two separate systems, but closely interrelated: an *anterior attentional system*, linked to environmental monitoring and detection of target stimuli, and a *posterior attentional system*, linked to the orientation of attention. More recent versions of this model describe three systems [28]-[30]:

1. **Alert/vigilance System**, connected to frontal and parietal regions, in particular of right hemisphere and its function consists in maintaining a state of activation;
2. **Orienting System** (posterior attentional system, PAS), consisting of posterior parietal and frontal cortex, temporoparietal junction (TPJ), thalamic nuclei such as pulvinar and reticular nuclei, and superior colliculus. Its functions include anchoring, disanchoring and shift of attention, selection of specific information from multiple sensory stimuli;
3. **Executive System** (anterior attentional system, AAS), consisting of prefrontal medial cortex, anterior cingulate cortex and supplementary motor area included. Its function

includes voluntary control of behavior, conscious elaboration of experience, handling novel situations, monitoring, and resolution of conflicts. These conflicts may include planning or decision-making, error detection execution of new responses, inhibitory control, self-regulation, involvement in stressful conditions. It is proposed that the anterior cingulate cortex (ACC) has a crucial role in monitoring the environment, detection of target stimuli appearance and resolution of conflicts between stimuli.

Furthermore, Corbetta and Shulman [31], by incorporating several recent studies, have proposed that the cortical control of attention is divided into two functionally divided but interacting systems (Figure 6 a-b):

a) **Dorsal Frontoparietal Network** (top-down, endogenous attention), is guided by cognition; it is involved in control of goal-driven attention, preparation and application of relevant stimuli selection. In dorsal frontal regions, this system includes frontal eye fields (FEF) and medial and lateral frontal cortex while, in dorsal parietal regions, includes the intraparietal sulcus (IPS) and superior parietal lobule (SPL).
b) **Ventral Frontoparietal Network** (bottom-up, exogenous attention), is guided by perception and is a stimulus-driven attentional system; it is involved in disengagement and re-orienting of attention towards salient or unexpected stimuli. The attentional shifts are automated. The areas involved are temporoparietal junction (TPJ), inferior parietal lobule (IPL), superior temporal gyrus (STG) and ventral frontal cortex (VFC), in particular, inferior and middle frontal gyrus (IFG, MFG).

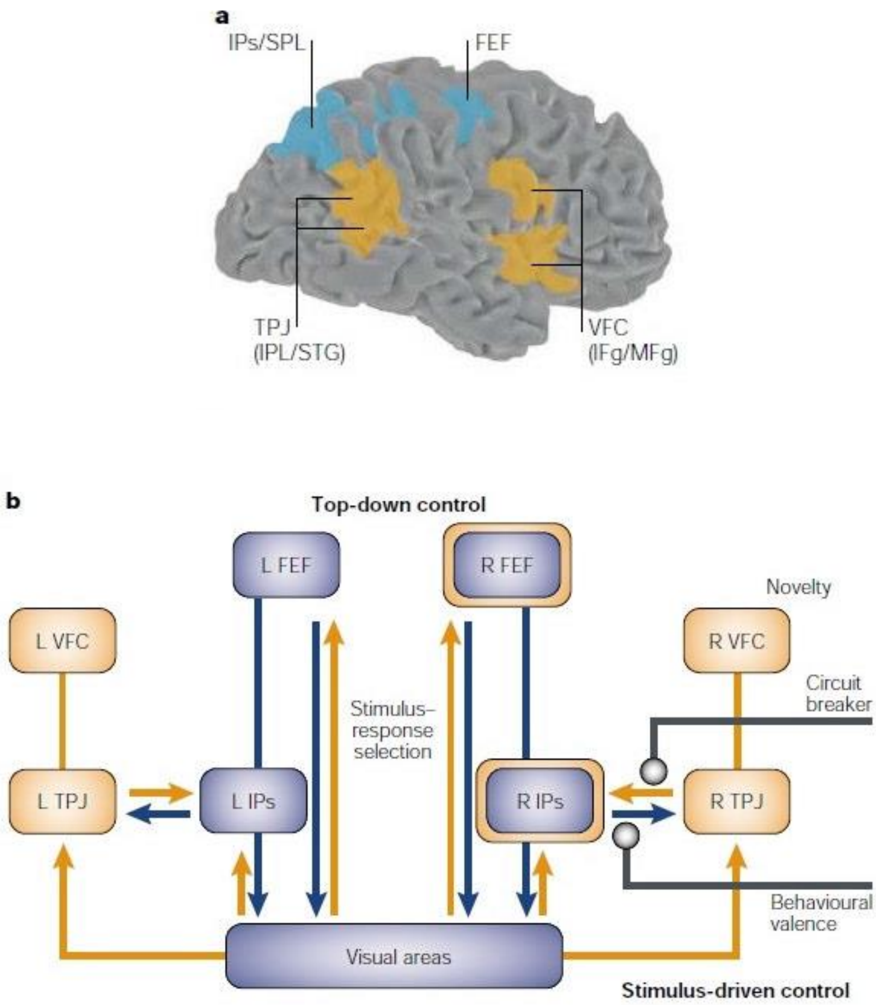

Figure 6 a-b – Neuroanatomical model of attentional control:

a. The dorsal frontoparietal network that controls endogenous shifts of attention (blue) and the ventral frontoparietal network, lateralized to the right, responsible for re-orienting and capture of exogenous attention (orange).

b. A combined model of endogenous-exogenous control of attention in which the dorsal network FEF-IPS is involved in top-down control of visual areas (blue) and the ventral network TPJ-VFC is involved in stimulus driven control (orange). The IPS and FEF are modulated by stimulus-driven control as well. The connection between TPJ and IPS interrupts ongoing top-down control when unexpected stimuli are detected. Behavioural valence is mediated by direct or indirect connections (not shown) between IPS and TPJ. VFC might be involved in novelty detection. The image above is modified from (Corbetta and Shulman, 2002).

The three levels of cognitive control can be connected to the attentional models mentioned above and used for the investigation of neurophysiological correlates of the SRK taxonomy. Indeed, among the cognitive neuropsychologists, it has been hypothesized a mechanism with the function of programming and control cognitive processes in relation to priorities, goals and external conditions. This mechanism called *Central Executive* provides a higher-level processing in a hierarchical organization. Since the central executive has a limited capacity, many routine operations should be delegated to mechanisms that operate automatically, regardless of the voluntary attention costly in terms of effort.

An automatic process [32] consists in the activation, on the base of appropriate inputs, of a learned sequence of elements, which proceeds without intentional attention, i.e. without the active control by the subject. On the contrary, a controlled process has limited capacity and requires continuous effort and monitoring by the subject. It works in serial mode, drawing on the stock of short-term memory. The automation (or proceduralisation) is facilitated by practice, which makes the process faster, parallel, with less demand for mental load. An example is driving a car, in which processes before “controlled”, subsequently become largely automated, because various operations are performed without the use of conscious attention. Anyway, special cases, such as using a new car or writing in a foreign language, require the return to a controlled process, even if those tasks would be automated in usual conditions. However, it should be remembered that attention does not always coincide with controlled process: the automatic process also focuses attention on certain stimuli, selecting among other not-relevant stimuli for the task, and keeps on focusing them for the necessary time.

Neuman [33] pointed out that the automatic process is not completely uncontrolled, but rather control is below the threshold of consciousness. Norman and Shallice [34] distinguished between processes totally automatic and others partially automated, based on selection (in the absence of conscious or voluntary control) between the established schemes, competing (defined contention scheduling); the selection is based on immediate priorities dictated by learning or by context. Thus, it seems appropriate to distinguish between non-intentional attentional processes, involving minimal effort and self-perception of the subject, and intentional attention, conscious and limited capacity. The relationship between awareness and attention is therefore extremely complex. Several empirical studies [35]-[37] demonstrate how information can be processed in relation to their meaning even if no consciously attention is active. Information meaning can also be analyzed in absence of intentional control and therefore of consciousness.

Starting from the point of view that attentional mechanisms control the access to awareness [38], [39], different models tend to identify the function of attentional control with conscience (as central operative system of activation and self-monitoring). According to Allport [40] and Schmidt [41], [42], the intentionality, attention, control and awareness are the constitutive dimensions of consciousness. Other authors distinguish between consciousness of external reality and self-awareness or awareness of their own cognitive processes (meta-cognition), their emotions and their choices (Figure 7).

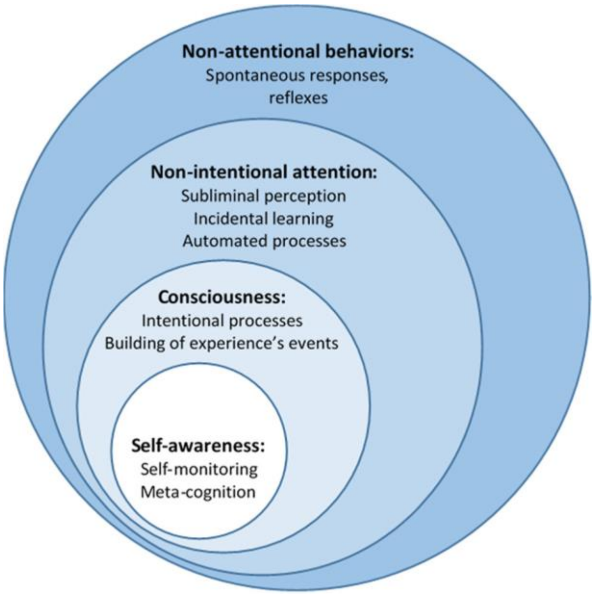

Figure 7 – A model of awareness levels

In conclusion, it is important to highlight that the level of attention plays a crucial role for the neurophysiological discrimination of the SRK levels in ATM domain. In fact, the skill-based behaviour has a nature purely motor, without conscious control which is activated only if the outcomes of an action do not match the goal. Differently, the rule-based behaviour is decisional but proceduralised, in the sense that requires a little more conscious attention on the preparation of the known sequence beforehand; while, the knowledge-based behaviour is characterised by executive/voluntary attentional control.

As this work is based on the detection of electroencephalographic signals, it has to be taken into account that higher activations of the EEG features, correlated to the attentional level, will represent higher attention demand, namely for rule- and knowledge-based behaviours.

4. PART II

4.1 EXPERIMENTAL PART

I. Introduction

As previously mentioned, according to the Rasmussen's framework, the human behaviour can be controlled at different levels of conscious control depending on the degree of familiarity with the task and the environment [1].

The skill-, rule- and knowledge-based behaviours can be considered as a dynamic system. Generally, the three levels work in parallel and the control over the behaviour continuously shifts from a level to another. Such a structure of the cognitive system makes the operator able to quickly react to the environmental changes, to deal with ambiguous situations, to solve familiar or unfamiliar problems and to set new problems with new plans in an efficient and flexible way.

Specifically, the skill-based behaviour is characterized by the lowest level of conscious monitoring or attentional control, since is mostly composed of highly routinized and automated actions. In ATM environment, most of the controller's observable tasks are skill-based, for example cursor positioning, command entry, use of phraseology, etc.

On the other hand, the rule-based behaviour requires some degrees of conscious involvement or attentional control than the skill level. In fact, the situation assessment leads the controller to the recognition and application of specific procedures to particular familiar situations. Examples of events implemented at the rule level are typical control task, such as rerouting, conflicts detection and management, coordination, etc.

The controller shifts to the knowledge-based level of behaviour when needs to face with unfamiliar situations, where no solutions are already available. At this level, the attentional control is almost completely conscious when the controller carries out his/her tasks; new plans must be generated because existing procedures are inadequate to handle unfamiliar and rare events. This would also occur in a situation where a student controller is performing the task (e.g. a trainee at the beginning of training) or where an expert is facing with a completely novel situation. In both cases, the mental effort exerted would be considerable for the situation assessment and the execution of the action. Furthermore, the controller would need to review the results of the current action before proceeding with other actions. The whole process could make the responses slower than normal [43].

So, this framework of human performance is a useful means to figure out how humans can deal with complex situations and is a powerful framework to orient design and evaluation of new interface system as well.

The main objective of this research is to understand if it is possible to define reliable and valid neurophysiological measurements (or indicators) for the identification of the three levels of cognitive control of behaviour, proposed by the SRK model, by means of the analysis of Experts and Students Air Traffic Controllers' brain activity while carrying out realistic ATM scenarios. Specifically, the aim is to characterize the three behaviours in terms of "pure" cognitive engagement by considering only brain features linked to cognitive processes, such as attention, information processing, decision-making, and working memory. The motor brain features (e.g. sensory premotor cortex) are not considered for not differentiating the S-R-K behaviours on the base of different amount of movements (hands or feet).

The next paragraphs will describe the whole steps performed, starting from the multi-dimensional approach, the methodology and materials used, the experimental phase which was carried out for the validation of the hypothesis generated, until the discussion of the results obtained.

II. Methods and materials

From cognitive functions to the SRK levels of cognitive control

To our understanding, there is no literature available about a direct correlation between the SRK framework and neurophysiological features. So, in order to reduce this gap, a multidisciplinary approach was used to achieve an exhaustive overview on this relevant Human Factors concept in ATM domain.

As shown in Figure 8, a literature review was performed for the identification of which cognitive functions and brain areas are likely to be involved in the three levels of cognitive control of behaviour. After, we selected the EEG frequency bands – connected to the identified cognitive functions – by which objectively describe the three levels of behaviour (blue arrows).

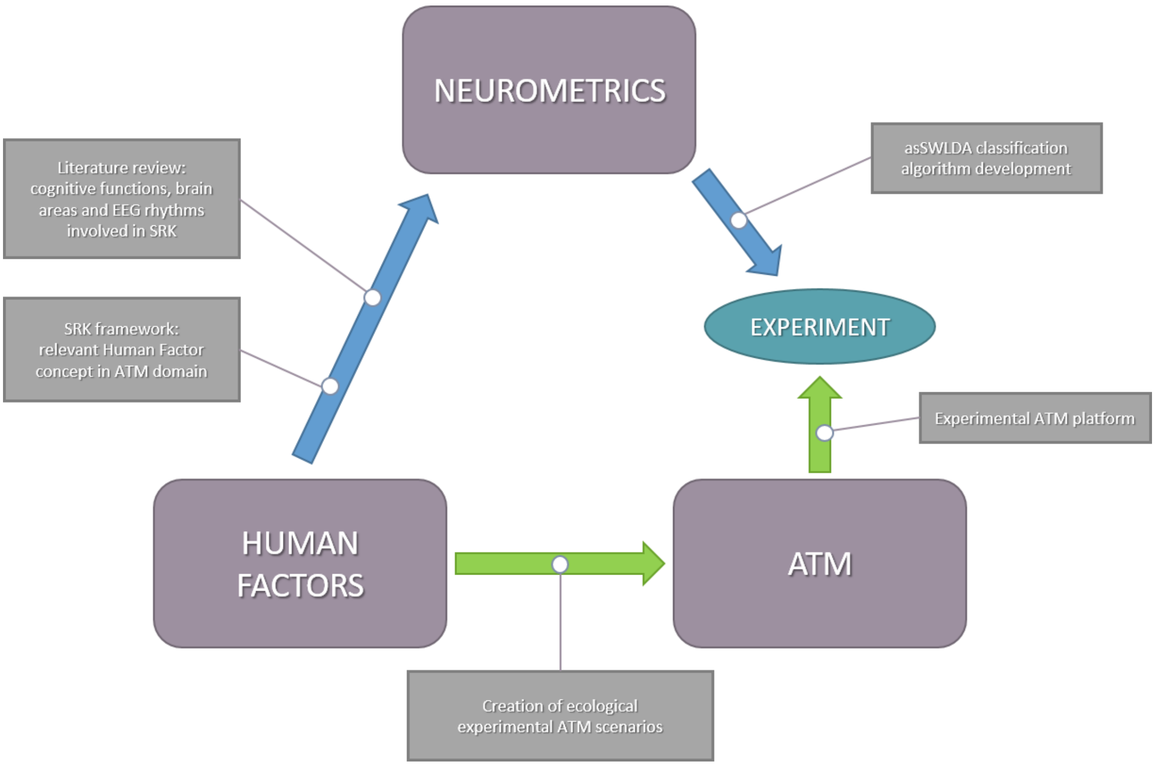

Figure 8 – Multidisciplinary approach used in the research

Simultaneously, an experimental ATM environment was set up for the assessment of the induced behaviours in the controllers (green arrows). Finally, the experiments were performed in order to validate the hypothesis formulated and verify if the selected brain features were able to discriminate the three levels of cognitive control of behaviour.

Different cognitive processes and levels of automatism are implicated in the SRK behaviours and each of them requires different cognitive effort related to specific operational conditions. As mentioned before, the skill level of control is based on highly routinized and automated actions, while the rule level is based on the identification and subsequent application of the right procedures. In other words, the rule behaviour could be considered as long-term memory access + automated actions (skill behaviour). At a knowledge level of control, the operator has to comprehend the current situation, elaborate and execute a new appropriate plan of actions. Thus, the knowledge behaviour can be considered as information processing + decision making + procedures selection (rule behaviour) + automated actions (skill behaviour). Besides, to maintain the realism of an ATM task, it was not possible to create absolute “pure” S, R and K events because the three levels continuously overlap during the work of the controller, so they would always show some contributes derived from the others. To measure and quantify the three levels of control in realistic conditions, the SRK events created ad hoc were inserted into an ATM scenario with different complexity levels, where the task difficulty (or mental workload) varied over time to simulate realistic air-traffic situations.

Brain features for the discrimination of the SRK levels: a literature review

Generally, the cognitive activities are associated with different activations over specific brain structures [44]. Indeed, the literature indicates that an increase in the demand of executive control (attention and working memory [45]-[47]) as well as when the mental workload demand [48]-[55] and task complexity [56]-[59] are high, an increase of the EEG activity can be observed, in particular in theta band over frontal cortex areas. Similar enhancement can also be observed with the involvement of decision-making (e.g. resolution of conflicts and error detection [60]) and problem-solving processes [61].

Moreover, several studies highlight the potential role of theta rhythms, engaged in the hippocampus/PFC (prefrontal cortex) interaction, during memory consolidation [62]-[66] and in induction of long-term plasticity [67]-[69].

It is widely accepted that memory consolidation process (e.g. procedural memory formation) is composed of two subsequent phases [70]-[73]:

1. The **encoding of experience** supported by hippocampus and occurs within the first minutes-to-hours after training, characterized by rapid improvement in performance.
2. The **memory consolidation** which involves the reactivation of neural circuits and occurs after training. This second phase requires longer time. During consolidation, memories are reorganized and hippocampus-dependent initial memories may become hippocampal independent [70]-[74].

Processes of reactivation of memories lead to renewed consolidation each time reactivations occur, enhancing the first consolidated memory representation, and converting it into a long-lasting stable memory trace [71]. Delayed additional gains occur after the second phase, even without additional practice [72]. Neural oscillations, in general, have been assumed to play a central role in cognitive processes and specific states of phase synchronization are considered a mechanism of increased communication between regions [75]-[77]. In fact, several evidences suggest that theta oscillations play an important role in formation of memory: for example, they are typical of hippocampal activity, upon memory encoding, generating oscillations which can propagate to other brain structures, in sustaining memory consolidation and are thought to play a critical role in the induction of long-term plasticity associated with memory consolidation [78], [79]. Theta rhythms are correlated with episodic and semantic memory [80]-[82] and are involved in learning and memory within the mPFC (medial prefrontal cortex) and hippocampal system [83]-[85]. Several studies indicate theta synchronization as a mechanism underlying communication between the hippocampus, the ventromedial prefrontal cortex and remote memory areas, during consolidation. The underlying mechanism is still not clear, but a tentative to explain it is shown in the *System-level Memory Consolidation Theory* [86]. The theory suggests the hippocampus is strongly activated at the first stages of memory related neocortical formations, but gradually they become independent from hippocampal activations, and consolidation correlates with increased activation in the ventromedial prefrontal cortex (vmPFC). This region seems to link the neocortical representational areas in remote memory [74], [86]. The theory implies the exchange of information in a network of brain areas where the centre is the hippocampus and the connected areas include the neocortex and other structures such as amygdala and striatum [74]-[87]. The interaction between hippocampus and striatum reflects the interaction between hippocampus and neocortex, and theta oscillations are likely to be associated with the regulation of information exchange between hippocampus and striatum [87]-[89] which is involved in learning beyond memory consolidation and is related to individual variations in learning performance [90]. Furthermore, the exchange of information extends to relatively distant sensory and associative areas of parietal cortex, which are also associated with theta oscillations [91]. In addition, parietal theta synchronization was also found to be correlated with retrieval [69], [92]. Therefore, our hypothesis was based on the idea that an enhancement of parietal theta activation could be considered as a signal of memory consolidation since it sustains the exchange of information between the hippocampus and neocortex [93], [94].

On the other side, the alpha frequency band range is generally associated with attention [95]-[97], in fact, imaging researches sustain this concept by reporting attentional modulations in the pulvinar nucleus [98]-[100] and in the lateral geniculate nucleus [101], [102]. Neuper and Pfurtscheller [103] show that the event-related desynchronization (ERD) of EEG activity in alpha band reflects an increment in the level of neurons' excitability in the involved cortical areas, which could be related to an increase of information transfer in thalamocortical circuits. On the contrary, the event-related synchronization (ERS) of alpha activity (e.g. increases in alpha activity) seems to reflect a reduced state of active information processing in the underlying neuronal networks [104], representing the inhibitory aspect of alpha-band oscillations [105], [106].

As mentioned by Klimesch [107], a storage system called Knowledge System (KS) seems to have a specific link with the attentional processes and the alpha band activity. The author sustains that *suppression* and *selection* are two fundamental functions of attention, which enable selective access to the KS and operate with the inhibition timing function of alpha band activity [108], [109]. The KS includes not only the traditional Long-Term Memory (LTM), but any type of knowledge, including procedural and implicit perceptual knowledge. Processes such as perception, encoding, and recognition are guided by attention and closely related to the access of information in the KS [110], [111]. Two kinds of processes may provide access to this system: the continuous or the event-related. In the continuous process, the alpha band range reflects continuous semantic orientation, which represents the ability to be consciously oriented in time, space, and in relation of the meaning of all entities surrounding the individual [112]. This ability is knowledge-based and requires a certain level of attention, which means that the semantic orientation provides individual the capability to access stored information in a selective way; such information represent the meaning of sensory information and higher order information, for instance language, mathematics, and geography [113]-[115]. The selective access to the KS is thought to depends on the inhibiting task-irrelevant memory entries. Therefore, periods of prolonged access should be associated with ERS, reflecting an increment (i.e. synchronization) of alpha band activity [116]-[118].

As a result of the literature review exposed, some hypotheses were formulated for the discrimination of the three levels of behaviour by assessing the degree of information processing, working memory (frontal theta EEG rhythm) [56], [48]-[50], procedural memory (parietal theta EEG rhythm) [60], [62], and attention (frontal alpha EEG rhythm) [55], [96], [101], [107], during the execution of the S, R and K events. The brain activations supposed to characterize the SRK levels of behaviour are summarized in Table 1.

LEVELS OF COGNITIVE CONTROL	EEG RHYTHMS		
	FRONTAL THETA	PARIETAL THETA	FRONTAL ALPHA
SKILL	Lowest Synch	Lowest Synch	Desynch
RULE	Synch	Synch	Synch
KNOWLEDGE	Highest Synch	Highest Synch	Synch

Table 1 – Hypothesized SRK characterization by means of the selected EEG rhythms. The SRK levels of cognitive control were described in terms of variation from a reference condition: synch –synchronization; desynch –desynchronization.

Experimental subjects and experimental set up

A total of thirty-seven Air Traffic Controllers were involved in the experiment: 15 ATC Experts (40.41 ± 5.54 years old) and 22 ATC Students (23 ± 1.95 years old) of the final year of course from École Nationale de l'Aviation Civile (ENAC) in Toulouse, France. The ATCOs were selected in the attempt to have homogeneous experimental groups in terms of age, expertise, gender, background, competencies, and accordingly with subjects' availability. To provide an appropriate level of realism with the activities carried out by ATCOs in their operational environment, the experimental setup was designed by HF and ATCO Experts. The ATCOs were asked to perform an ATM scenario using a research simulator, an ATM platform developed by ENAC (Figure 9 a-b).

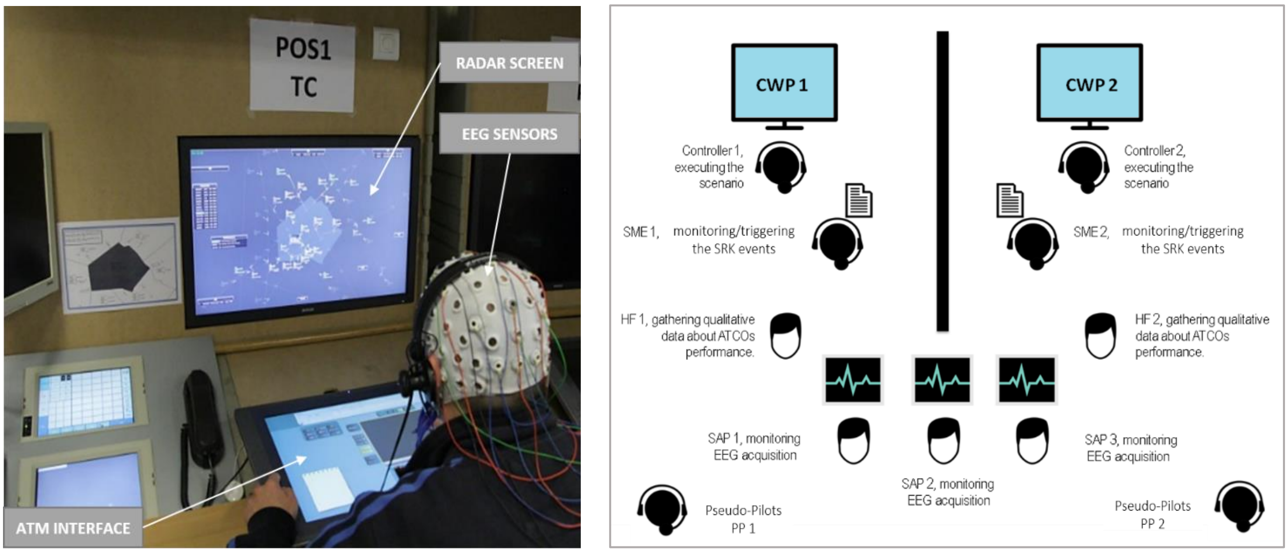

Figure 9 a-b – Experimental setup:

a) ATM platform developed and hosted at ENAC in Toulouse, France. The ATCO in front of the radar screen, wearing EEG sensors to record his/her brain activity during the execution of an ATM scenario;

b) a graphical representation of the experimental setup.

Each recording activity involved two ATCOs (Controller 1-2) executing the scenarios, two External Advisory ATC Experts (SME 1-2) monitoring and triggering SRK events and taking note of anything considered relevant, two Human Factors Experts (HF 1-2), briefing/debriefing sessions, monitoring the execution of simulation activities and collecting qualitative data on the controllers' performance, and three Neurophysiological Measurements Experts (SAP 1-2-3), positioning the technical equipment, monitoring and collecting the EEG signals. Two Pseudo-Pilots (PP 1-2) were also involved to simulate real pilots, flying the aircrafts under ATCOs control, and communicating with them via radio sector frequencies. Despite there were only two pseudo-pilots, the cabin noise and pilots' voice were modified with special tools so that the ATCOs heard different voices and cabin atmospheres for each aircraft. The ATM scenario was designed from real traffic samples used in the training program at ENAC. The traffic complexity was modulated by the *Number of aircraft* in the controlled sector, the *Traffic geometry*, and the *Number of conflicts* with the aim to define different air-traffic complexity levels, Easy (E), Medium (M) and Hard (H), and simulate realistic transitions among such conditions. The duration of the scenario was 45 minutes, while the E, M and H levels lasted 15 minutes each.

SRK events definition

A total of six SRK events were designed to produce the three conditions of cognitive control behaviour, Skill, Rule, and Knowledge. A Subject Matter Expert (SME) from Ente Nazionale di Assistenza al Volo (ENAV) in Rome, was involved in creating realistic and not disruptive SRK events for the simulation. Two triplets of SRK events (S1, R1, K1, and S2, R2, K2) were randomly included in the ATM scenario (Figure 10).

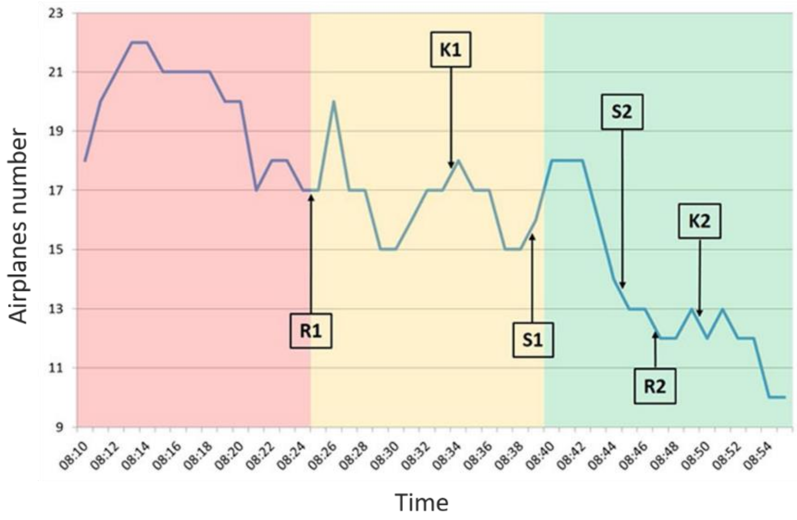

Figure 10 – Distribution of the SRK events along the scenario. The triplets of SRK events were inserted in a randomized sequence to avoid any habituation and expectation effects. No SRK events were inserted in the Hard condition for not generating unrealistic ATC conditions.

Specifically, three events were inserted in the E condition and three events in the M condition with the aim to check if the selected brain features were able to characterize the three levels of cognitive control of behaviour in realistic ATM settings. Anyway, the events were not inserted into the H condition of the scenarios, since the introduction of additional events could lead the complexity to an unacceptable level, generating too much disruption on the controllers' activity and possibly invalidating the realism of the task.

The SRK events were two types for each level of behaviour and were designed as in the following description:

1. The **Skill (S) events** were basically interactions with the interface during the execution of the task. Controllers were asked, by showing them a sheet with the instructions, to visualize the distance between two aircrafts (Distance event) or to display the Flight Plan Level (FPL) trajectory of each aircraft present in the controlled sector (Display Flight Plan event).

2. The **Rule (R) events** were mainly control-tasks and conflicts-resolutions, during which controllers were also performing skill-events (interaction with the interface). In the two Conflict events, controllers had to detect and solve a conflict by using the menu of the interface, assign new altitudes and headings, and eventually to call the pilots asking information about their FPLs. The hypothesis was that conflict detection task represented a familiar situation for controllers. Therefore, they should recognize the correct procedures and solutions and then apply them to solve the conflict.
3. The **Knowledge (K) events** were represented by unfamiliar and unusual situations which generated a certain state of uncertainty, leading the controllers to require time to analyse the situation and find out the proper procedure to cope with the unexpected event. In other words, the controllers initially had to evaluate the situation, identify the unusual situations, and then come back to the rule-based level for adopting the right procedures. In the first knowledge-based event (Deviation event), an aircraft deviated from the route filled in the initial FPL. An alarm was displayed on the radar interface with the aim to make the controller focusing on the aircraft (a/c), checking its manoeuvres, and detecting that something was happening. Once contacted, the pilot claimed to be on the right FPL. Controllers needed to understand if there was a problem with the system or a pilot's error. In the second knowledge-based event (Unidentified Flying Object – UFO), the Pseudo-Pilot reported an unknown-traffic detected by the Traffic Collision Avoidance System (TCAS) and a TCAS resolution advisory to avoid a mid-air collision. This unknown aircraft has not been displayed on the controller's radar image, who was supposed to understand the situation and to ask additional information to the pilot of the considered aircraft. After the avoidance

manoeuvre (e.g. descent), the pseudo-pilot had to ask for his previous flight-level, which never changed on controller's HMI because the pseudo-pilots were instructed to act during this event. The ATCO could not observe neither the aircraft responsible of the TCAS advisory nor the implementation of the avoidance manoeuvre.

Table 2 summarizes the description of the SRK events, in the proposed order of the scenario, showing how the type of events was not exactly the same in terms of requested actions, in order to make the results more robust to possible confound on brain activations while accomplishing the SRK events. Finally, along the execution of the SRK events, SMEs (sat behind the ATCOs) checked if the controllers performed correctly the proposed events and they confirmed that all the involved controllers, both Experts and Students, executed correctly the SRK events.

TYPE OF EVENT	DESCRIPTION	IMPLEMENTATION	EXPECTED CONTROLLER ACTIONS
R1 (Conflict)	Controllers have to detect and solve a conflict, using the pie menu to assign new altitudes and headings.	Flight DLH27R calls: "DLH27R, I would like to climb to FL370 to avoid a heavy turbulence".	Controller would observe his radar screen and then he would open the pie menu. Clicking on Confirm Flight Level (CFL), he would assign the new required altitude. Then, to avoid a conflict between flight DLH27R and flight AFR629, he would use the pie menu to change the flight AFR629 altitude to FL360, and eventually, he would call the pilots to ask information about their FPLs.
K1 (Deviation)	Controllers are asked to face with unexpected situation, in which an aircraft changes its route respect to the declared FPL. Controllers have to detect the manoeuvres and check the aircraft (a/c) FPL on the RADAR interface to evaluate if something is going wrong.	Flight FGJNH would turn to HARRY instead of flying the original flight route.	After the detection of the aircraft unexpected manoeuvre, Controller would call flight FGJNH asking for explanations. Then he would check the original FPL to evaluate if this latter is correct or if something is going wrong. After flight FGJNH call, once clarified the situation, he would give the pilots instructions to move back to the original FPL.
S1 (Distance)	Controllers were asked to measure the distance between two aircrafts using the "alidade" tool. The alidade tool is used to measure the distance between two points on the radar image. The user selects the origin of the alidade and the tool will draw a line which follows the cursor and indicates the distance from the origin.	SME asks the Controller to measure the distance between flight NJE123 and flight IBE692.	Controller would use the alidade tool, clicking on flight NJE123 and dragging the cursor to Flight IBE692; the system would provide the distance between such aircrafts.
S2 (Display FPs)	SME will trigger the event showing the Controller a sheet with the instruction to visualize the Flight Plan (FPL) trajectory of each assumed aircraft. Controller have then to use the pie menu of the WACOM interface and select the route option for each aircraft.	SME shows the Controller a paper with the following instruction: "Please visualize the FPL trajectory for each assumed aircraft on your radar screen. This is just a system check. Thank you".	Controller would open the pie menu and select the route option for each aircraft.
R2 (Conflict)	Controller has to detect and solve a conflict, using the pie menu to assign new altitudes and headings.	Flight ICE873 calls: "ICE873, I would like to descend to FL370 to avoid a heavy turbulence".	Controller would observe his radar screen and then he would open the pie menu. Clicking on CFL option, he would assign the new required altitude, and eventually, he would call the pilots to ask information about their FPLs. Expected conflict with flight TAP369 at FL380.
K2 (UFO)	Controller is asked to verify an unknown traffic detected by the Traffic Collision Avoidance System (TCAS), to avoid a mid-air collision. After the avoidance manoeuvre, pilots report a different FPL with respect to what provided by the RADAR interface.	Flight RAE1789 calls: "I have a traffic advisory. I'll call you back" After 10 seconds, with emphasis: "TCAS resolution, we are descending". After 10 seconds, a/c will call "cleared of conflict, we are at FL380". (without really change the FPL).	Controller would verify this unknown traffic on his RADAR interface, but he would not see any aircraft. Then Controller would eventually check the RADAR interface to verify if there is some activated filters. After a/c descent, the Controller would still see FL390 on the a/c label, probably would ask to a/c to check and confirm its FPL.

Table 2 – Detailed description of the SRK events designed to induce Skill, Rule and Knowledge behaviours in the controllers during the execution of the ATM scenario.

Neurophysiological signals recording and pre-processing

The neurophysiological signals were recorded using the digital monitoring BEmicro system (EBNeuro system, Italy). The nine EEG channels (FPz, F3, Fz, F4, AF3, AF4, P3, Pz, and P4) were collected with a sampling frequency of 256 (Hz). All the EEG electrodes were referenced to both the earlobes, grounded to the mastoids, and the impedances of the electrodes were kept below 10 (kΩ). The acquired EEG signals were digitally band-pass filtered by a 5th order Butterworth filter (low-pass filter cut-off frequency: 30 (Hz), high-pass filter cut-off frequency: 1 (Hz)). The eye-blink artifacts were removed from the EEG using the Reblinca method [119]. Specifically, with respect to other regressive algorithms (e.g. Gratton method [120]), the Reblinca method presents the advantages to preserve EEG information in blink-free signal segments by using a specific threshold criterion that automatically recognize the occurrence of an eye-blink, and only in this case the method corrects the EEG signals. If there is not any blink, the method does not introduce any changes into the EEG signal. In addition, the Reblinca method does not require any EOG signal(s). The EEG signal was then segmented in 2 second-epochs, shifted of 0.125 (sec), with the aim to have both a high number of observations in comparison with the number of variables, and to respect the condition of stationarity of the EEG signal [121]. In fact, the latter one is necessary to proceed with the spectral analysis of the signal. For other sources of artifacts, specific procedures of the EEGLAB toolbox have been applied [122]. Three methods were used: the threshold criterion, the trend estimation and the sample-to-sample difference. In the threshold criterion, an EEG epoch was marked as “artifact” if the EEG amplitude was higher than ±100 (μV). In the trend estimation, the EEG epoch was interpolated to check the slope of the trend within the considered epoch. If such slope was higher than 3 (μV/epoch) (non-physiological variation), the considered epoch was marked as "artifact". The last check calculated the difference between consecutive EEG samples. If such difference, in terms of amplitude, was higher than 25 (μV), it meant that an abrupt variation (non-physiological) happened, thus it was marked as "artifact". At the end, the EEG epoch marked as "artifact" was removed with the aim to have a clean EEG dataset from which estimating the brain parameters for the different analyses. The Power Spectral Density (PSD) has then been estimated by using the Fast Fourier Transform (FFT) in the EEG frequency bands defined for each subject by the estimation of the Individual Alpha Frequency (IAF) value [123]. By segmenting the EEG signal, we achieved an average number of 224 epochs, for a 30 seconds-long event, with an average rejection rate of 17.3 ± 13.6%. In addition, by using 2 second-long Hanning windows for the PSD estimation, we obtained a frequency resolution of 0.5 (Hz). Thus, according to the definition of theta [IAF - 6 ÷ IAF - 2] and alpha [IAF - 2 ÷ IAF + 2] EEG bands, we obtained 17 frequency bins, i.e. 17 PSD values for each EEG channel. Furthermore, the Baseline (brain activity during a minute of rest conditions, that is, closed eyes - OC) and the Reference (ATCOs looked at the radar screen without reacting for 3 minutes, where two no-colliding airplanes were presented - REF) conditions were recorded before starting with the ATM simulations. The OC condition was used for the IAF estimation, while the REF condition was used to evaluate the PSDs variations, with respect to the considered experimental condition, within the S, R and K events in terms of z-score [124] values.

The results proposed in the following sections will be represented as z-score values, thus values (y-axis) of zero mean that there are no differences, in terms of PSD, between the considered experimental condition (S, R and K) with respect to the REF one. Positive z-score values mean synchronization of the considered EEG rhythm (PSD increment), while negative z-score values mean desynchronization of the considered EEG rhythm (PSD decrement).

SRK neurophysiological characterization

The Power Spectral Density (PSD) was estimated for different brain features, namely frontal and parietal theta, and frontal alpha EEG rhythms; the analysis of their spectral information was performed to assess if they could be used for the neurophysiological characterization of the SRK levels.

One-way repeated measures ANOVAs were performed for each brain rhythm with the SRK, (3 levels: Skill, Rule and Knowledge) as within factor, and with the PSD as independent variable.

SRK discrimination: machine-learning analysis

The classification algorithm automatic stop StepWise Linear Discriminant Analysis – asSWLDA [53], [57] – was used to select the most relevant brain spectral features. Specifically, the frontal and parietal theta, and frontal alpha EEG rhythms were used for the calibration of the asSWLDA [125] to characterize and discriminate the different cognitive control levels (SRK) during the execution of the ATM simulation. Therefore, the asSWLDA algorithm was calibrated by using brain features (i.e. PSD epochs) extracted within the considered spectral domain (frontal and parietal theta, and frontal alpha) from one triplet of SRK events (S1, R1, K1), and then tested on the remaining triplet (S2, R2, K2), and vice versa.

For each testing triplet, the Area Under Curve (AUC) values were calculated of the Receiver Operating Characteristic – ROC [126] by considering couples between SRK distributions. The AUC values related to the discrimination accuracy between the three couples of conditions (S vs R, S vs K, R vs K) were calculated and analysed for each ATCO.

To test the effectiveness of the algorithm, and that the SRK discrimination would not be due to chance, for each couple of conditions (S vs R, R vs K, S vs K) we compared the AUC distributions obtained from the experimental data of the ATCOs (Measured AUC), with a random distribution calculated for each specific couple (Random AUC), situation corresponding to the random classification. We performed all the possible permutations along both the calibrating and testing dataset [127], [128]. In this regard, we shuffled the SRK labels for the ATCO Experts related data, and then we calculated the AUC values between couples of conditions (e.g. S vs R) considering two cases: one in which the right labels were used (Measured AUC), and the other in which the labels were randomly set (Random AUC). The Random AUC distributions were compared with the Measured AUC by using three two tailed student t-tests ($\alpha = 0.05$), to demonstrate the reliability of the algorithm. For the ATCO Students, we were unable to perform a three-class analysis, because most of them missed the first knowledge-based event (Deviation). In this regard, we considered only the rule and skill conditions. In detail, the asSWLDA was calibrated by using one couple (S1, R1) and the discrimination accuracy (AUC values) was tested on the remaining couple (S2, R2), and vice-versa. As consequence, the AUC distributions (Measured AUC, and Random AUC) were calculated only for the “S vs R” comparison.

Comparison between ATCO Experts and Students

Two-tailed unpaired t-tests (α = 0.05) were performed to compare the discrimination accuracy (i.e. AUC) between the skill and the rule conditions (the knowledge event was missed as quoted above) between the two groups (ATCO Experts and ATCO Students). The hypothesis was that the ATCO Students were not as skilled as the ATCO Experts, so that the skill-based events (that should be characterised by completely automated activities) could require a brain activation and attention as for the rule-based events. In this regard, the asSWLDA was calibrated by using one couple of conditions (S1, R1), and the AUC values were calculated on the remaining couple (S2, R2) and vice-versa, both for the ATCO Experts and Students. In addition, one-way ANOVAs were performed on the frontal and parietal theta, and frontal alpha PSDs with the aim to assess eventual differences between the two groups (between factor RANK; 2 levels: Experts and Students). Before every statistical analysis, the z-score transformation [129] was used to normalize the data. Furthermore, the most common brain features selected by the asSWLDA, within the single EEG band and in total, were analysed and compared between the two groups. In more detail, we assigned "1" to the selected features, and then we summed up the values over the cross-validation and ATCOs, separately for the Experts and Students, to finally calculate the average rate by which each feature was picked for the SRK events discrimination. For example, if a frequency bin, within the frequency range "theta + alpha band", was selected 5 times for all the ATC Experts, it was then divided by the total number of cross-validations (2 cross-validations) multiplied by the number of the considered ATCOs (15 Experts). Therefore, the final percentage corresponding to such a bin was (5/ (2*15)) *100 = 16.67%. Two-tailed unpaired t-tests were then performed to assess possible differences between the ATCO groups in terms of selected brain features.

III. Results

SRK neurophysiological characterization

The ANOVA on the frontal theta PSD (Figure 11) demonstrated that this brain feature changed significantly ($F (2, 64) = 17.01$; $p < 10-5$) among the S, R and K conditions; this means that it could be used for the discrimination of the three levels of behaviour. Specifically, the post-hoc test reported high discriminability of the skill event compared to the other two ($p < 0.00006$), and the difference between the knowledge and the skill events ($p < 0.0002$). On the contrary, the rule and the knowledge conditions did not differ significantly ($p = 0.3$).

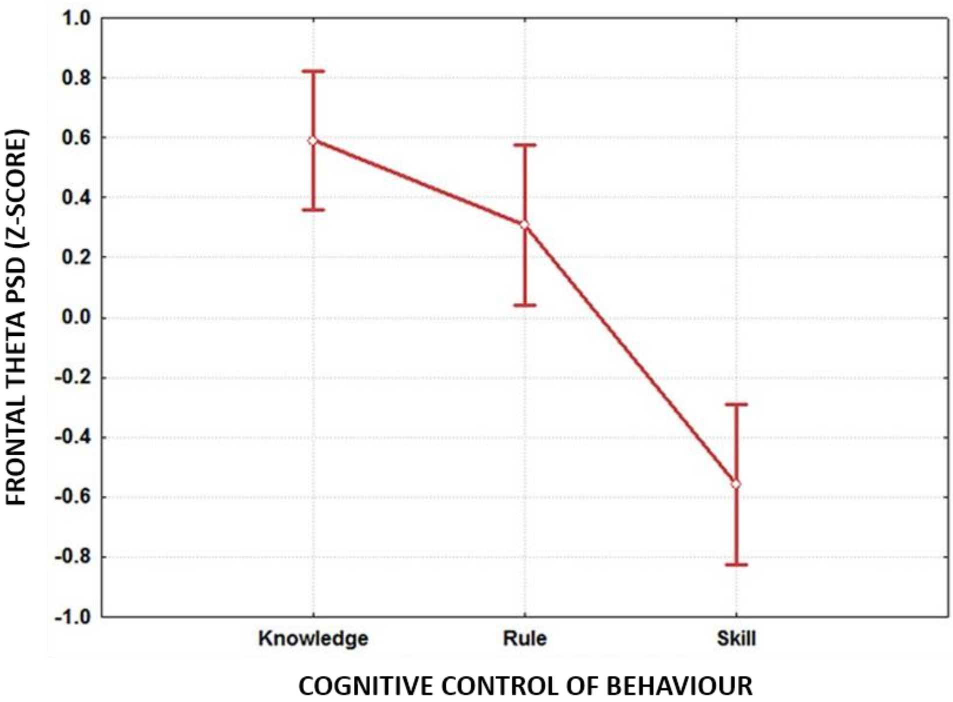

Figure 11 – The chart represents the results of the ANOVA analysis on the frontal theta PSD with the factor “SRK” of 3 levels (Skill, Rule and Knowledge). The results show that such brain feature could be used as SRK discriminant brain feature, as its PSD values are significantly different (p=0.000001) between the S, R and K levels.

Regarding the results of the ANOVA performed on the parietal theta PSD (Figure 12), it demonstrated that significantly changed across the SRK levels ($F (2, 64) = 4.11$; $p = 0.021$). The post-hoc reported that the parietal theta PSD could be used to discriminate accurately the skill from the knowledge level ($p < 0.002$). On the contrary, the parietal theta PSD did not change significantly between the rule – knowledge, and skill – rule levels ($p > 0.25$).

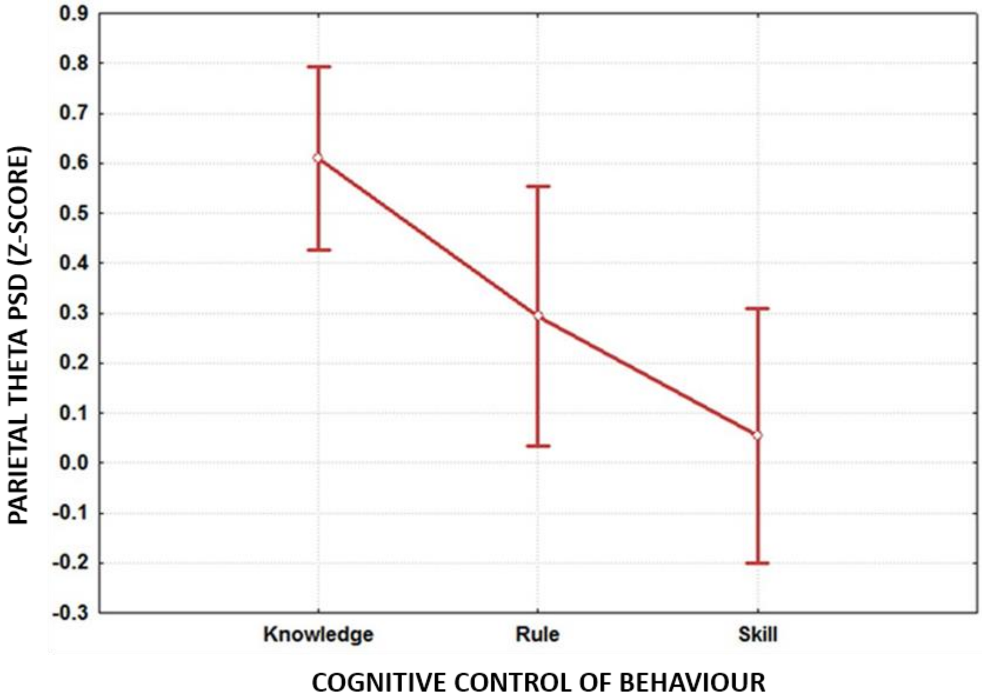

Figure 12 – The chart represents the results of the ANOVA analysis (CI=0.95) on the parietal theta PSD with the factor "SRK" of 3 levels (Skill, Rule and Knowledge). The results show that such brain feature could be used as SRK discriminant brain feature, as its PSD values are significantly different (p=0.02092) between the S, R and K levels.

The results of the ANOVA on the frontal alpha PSD (Figure 13) demonstrated a significant effect in the SRK discrimination ($F (2, 64) = 11.48$; $p < 10-4$), and the post-hoc test reported that the frontal alpha rhythm could be used to differentiate either the skill from the rule ($p = 0.0003$) and knowledge levels ($p = 0.0002$). On the contrary, the frontal alpha PSD did not change significantly between the knowledge and rule levels ($p > 0.8$).

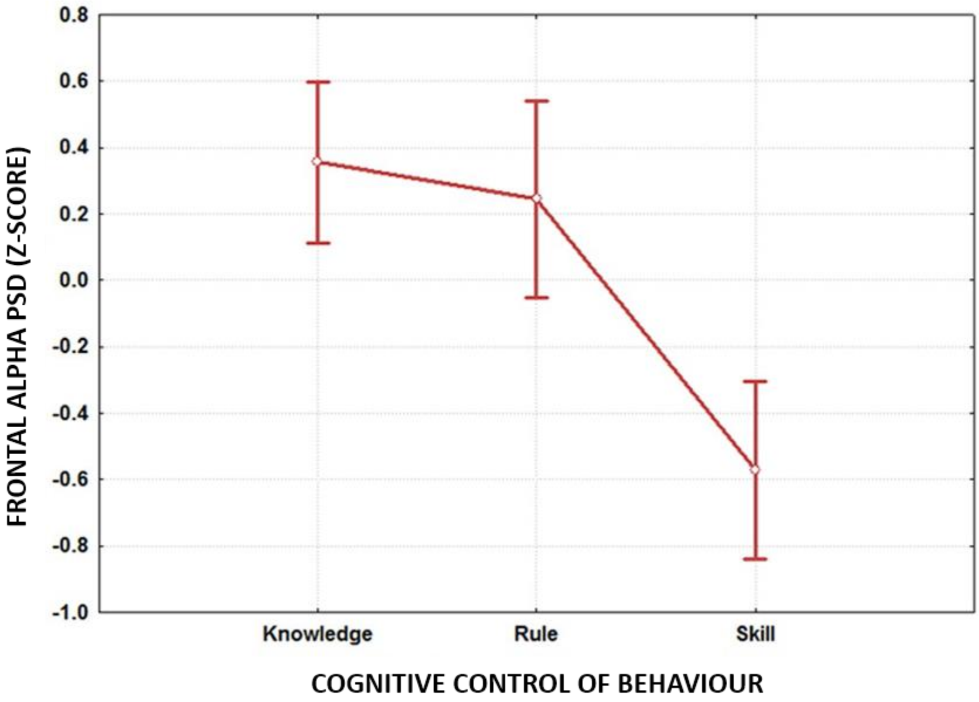

Figure 13 – The chart represents the results of the ANOVA analysis (CI=0.95) on the frontal alpha PSD with the factor "SRK" of 3 levels (Skill, Rule and Knowledge). The results show that such brain feature could be used as SRK discriminant brain feature, as its PSD values were significantly different (p=0.00006) between the S, R and K levels.

SRK discrimination: machine-learning approach

As previously mentioned, the asSWLDA was calibrated by using one triplet (S1, R1, K1) and the discrimination accuracy (AUC) was calculated by testing it on the remaining triplet (S2, R2, K2), and vice-versa. In detail, for each couple of conditions (S vs R, R vs K, S vs K) we shuffled the SRK labels and then calculated the AUC values considering a case in which the right labels were used (Measured AUC), and another case in which the labels were randomly set (Random AUC).

Referring on the results reported in the previous sections, the frontal and parietal theta, and frontal alpha EEG rhythms were defined as the frequency domain in which the asSWLDA classification model had to select the most significant features to discriminate the three levels of cognitive control of behaviour (SRK) from the chance level. Figure 14 shows the

Measured AUC (blue bars) from the Random AUC (yellow bars) for each ATCO (Experts on the top part of the image) averaged across all the possible labels combinations.

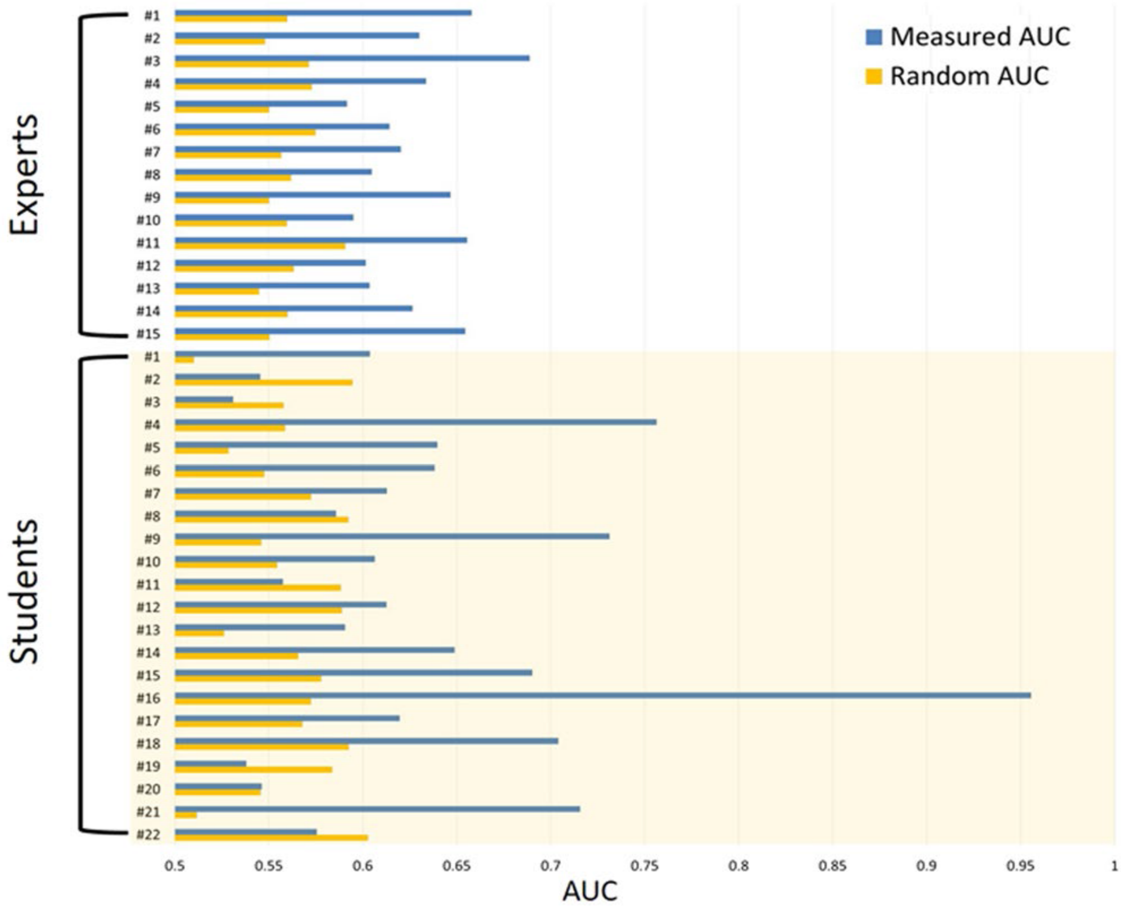

Figure 14 – Bars plot of the averaged Measured AUC (blue bars) across all the possible labels combinations compared to the Random AUC (yellow bars) for each ATCO. Specifically, the AUC values of the Experts are reported on the top of the image, while those of the Students are reported on the bottom.

ATCO Experts

The two-tailed paired t-tests ($\alpha = 0.05$) reported that all the Measured AUC (blue bars) distributions were significantly higher (left side of Figure 15) compared to the Random AUC (yellow bars) distributions (all $p < 0.002$).

ATCO Students

The two-tailed paired t-test (α = 0.05) reported that also for the ATCO Students all the Measured AUC (blue bars) distributions were significantly higher (right side of Figure 15) than the Random AUC (yellow bars) distributions (all $p < 0.05$).

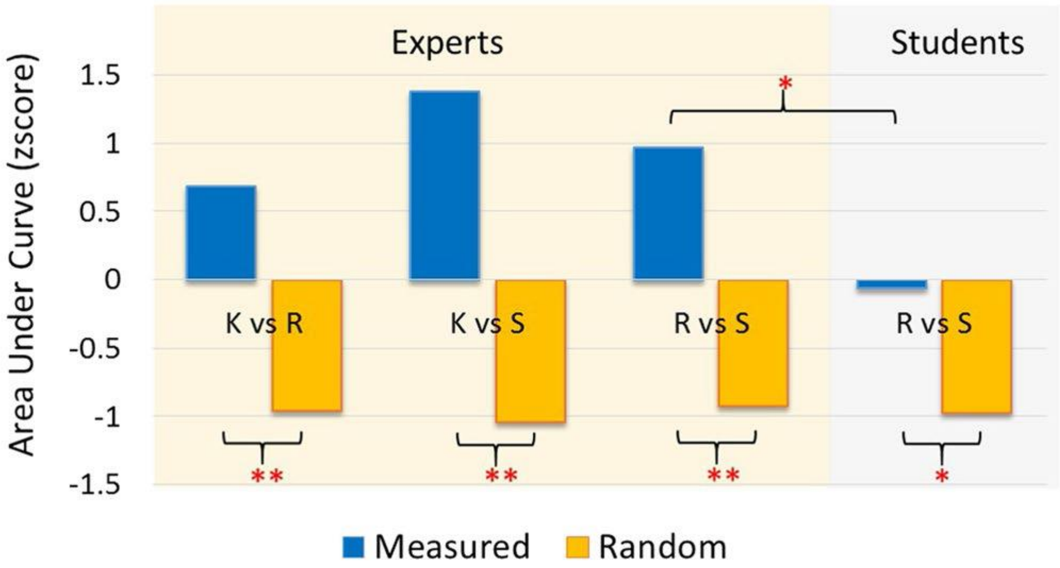

Figure 15 – Bars plot related to the z-score-normalized Measured AUC (blue bars) distributions and the Random AUC (yellow bars) distributions, achieved by the ATCO Experts (left side) and Students (right side), referred to the discrimination accuracy among the three couples of conditions (S vs R, S vs K, R vs K) for Experts, and S vs R for Students. The three cognitive control behaviours could be significantly discriminated for both the groups ($p < 0.05$). In addition, the results show how the S and R behaviours are significantly ($p < 0.05$) more discriminable for Experts than for Students ($p < 0.05$).

Comparison between ATCO Experts and ATCO Students

The bars plot chart (Figure 15) also shows the differences between the two ATCO groups in terms of z-score-normalized AUCs, indeed the ATCO Experts exhibited a significant higher ($p < 0.05$) discrimination accuracy compared to the ATCO Students. The trend may indicate how the levels of behaviour were better discriminable for Experts than for Students. In addition, the results performed on PSD values reported that the considered brain features could be used to recognize the level of expertise (Expert vs Student) with significant reliability (all $p < 0.03$). In fact, the one-way ANOVAs demonstrated significant differences between the group of ATCO Experts and ATCO Students in terms of brain activations, as shown in Figures 16, 17 and 18.

In more detail, the ATCO Students showed both higher frontal and parietal theta synchronization, respectively ($F(1, 32) = 9.14$; $p = 0.005$) and ($F(1, 32) = 10.97$; $p = 0.0023$), and a lower frontal alpha desynchronization ($F(1, 32) = 5.62$; $p = 0.024$) than the ATCO Experts.

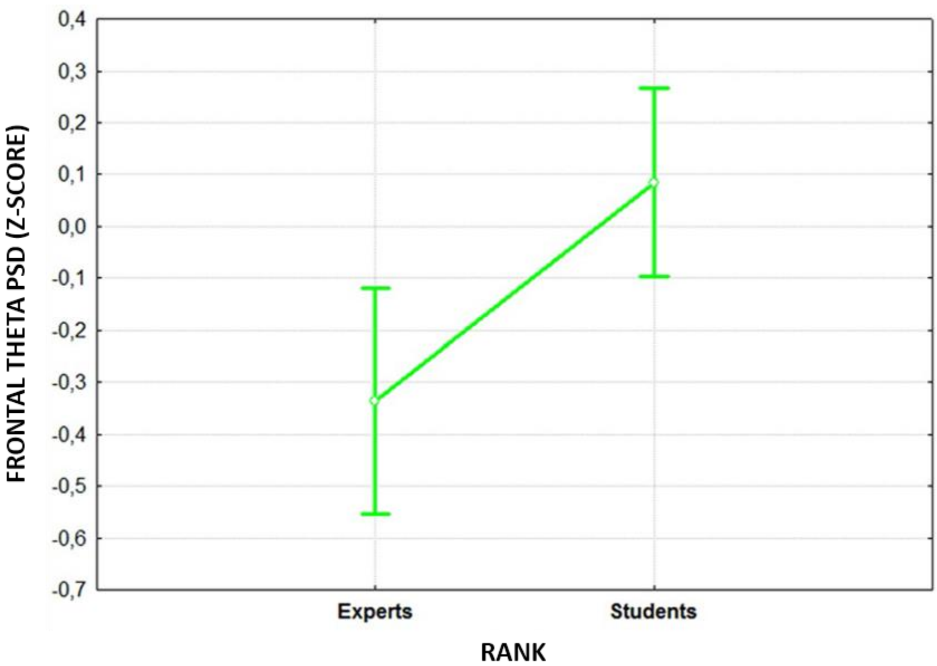

Figure 16 – The chart reports the results of the ANOVA analysis (CI = 0.95) on the frontal theta PSD with the factor "RANK" of 2 levels (Experts and Students). The results showed that the two groups are statistically different (p = 0.005) in terms of activation of the frontal theta rhythm when facing the same SRK events.

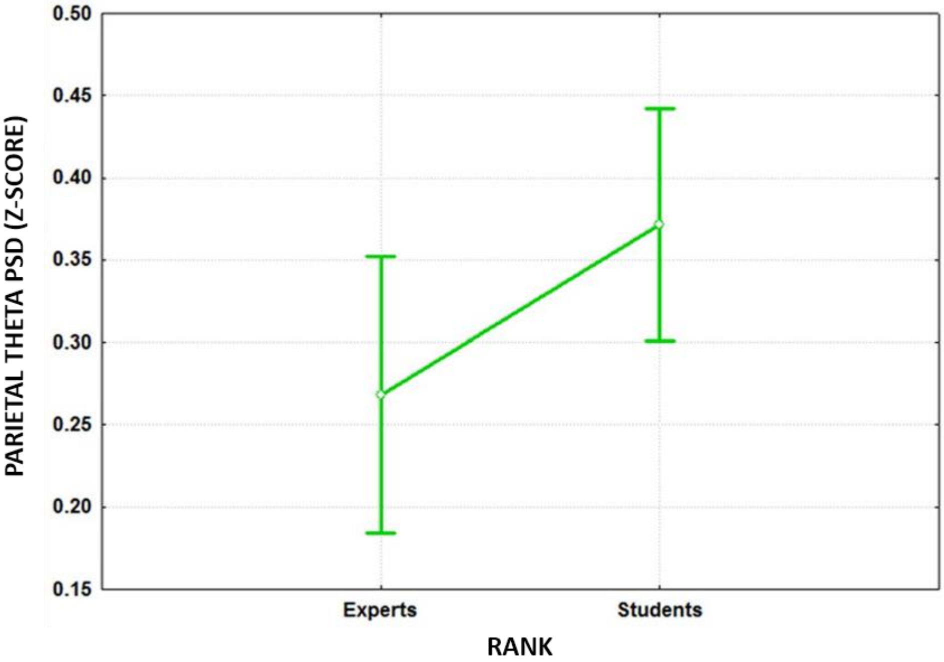

Figure 17 – The chart reports the results of the ANOVA analysis (CI = 0.95) on the parietal theta PSD with the factor "RANK" of 2 levels (Experts and Students). The results showed that the two groups are statistically different ($p = 0.0023$) in terms of activation of the parietal theta rhythm when facing the same S, R and K events.

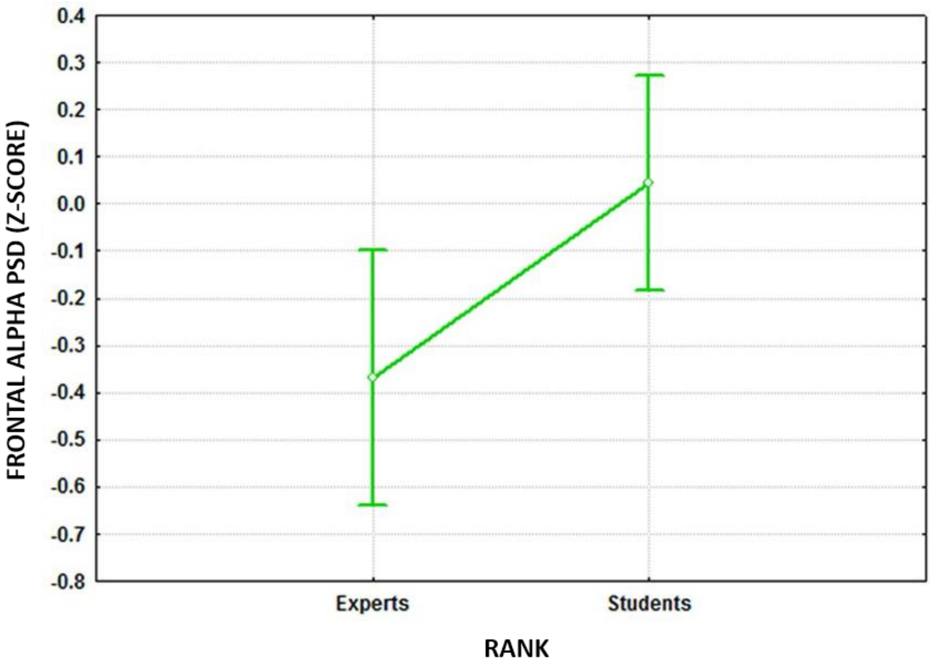

Figure 18 – The chart reports the results of the ANOVA analysis (CI = 0.95) on the frontal alpha PSD with the factor "RANK" of 2 levels (Experts and Students). The results showed that the two groups are statistically different ($p = 0.024$) in terms of activation of the frontal alpha rhythm when facing the same S, R and K events.

Selected brain features

Figures 19 and 20 represent respectively the selected brain features for the ATCO Experts and ATCO Students. The results showed that, on average, the selected brain features were 5.15 for the ATCO Experts, and 5.6 for the ATCO Students with no general statistical difference between them ($p = 0.59$). However, by observing the figures, it can be highlighted that the selected features over the frontal areas of the Experts were lower than for the Students.

Subsequently, two two-tailed unpaired t-tests were carried out, in a separate way, on the features selected within the frontal EEG channels, and within the parietal EEG channels. The results reported a clear trend (even if not strictly significant $p = 0.07$) in the number of selected features over the frontal areas, since they were significantly higher for the ATCO Students (Figure 20) than for the ATCO Experts (Figure 19), while no difference was found among the selected parietal features ($p = 0.63$).

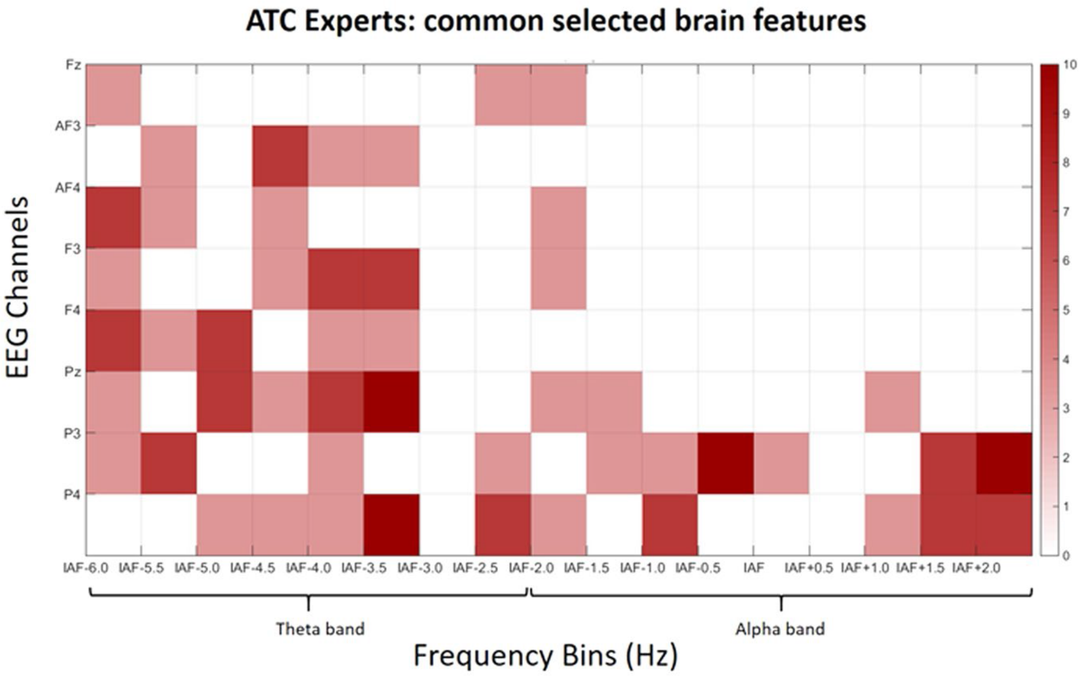

Figure 19 – Percentages related to the brain features most commonly selected by the asSWLDA across the ATCO Experts for the SRK-based cognitive control behaviours discrimination. White colour means that brain features were not selected at all. On the contrary, the red colours mean that the brain features were selected more frequently.

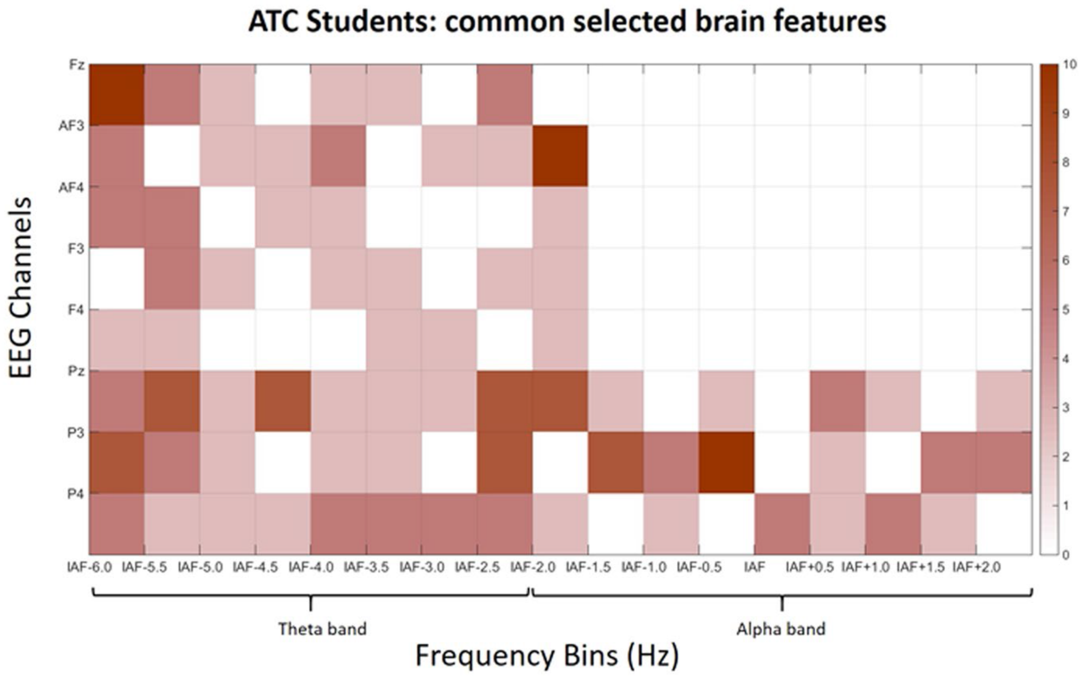

Figure 20 – Percentages related to the brain features most commonly selected by the asSWLDA across the ATCO Students for the SRK-based cognitive control behaviours discrimination. White colour means that brain features were not selected at all. On the contrary, the red colours mean that the brain features were selected more frequently.

IV. Discussion

In our understanding, there is no evidence so far of studies which consider the Skill, Rule and Knowledge cognitive model from a neurophysiological point of view, despite many attempts were done in a Human Factors domain for representing the different levels of human performance [32], [34], [130]-[132].

In this work, a multidisciplinary approach [133] was adopted, characterised by several steps which started with an extensive literature review for the identification of the main cognitive processes related to the S, R and K levels of cognitive control of behaviour.

Then, the three levels were defined considering only the cognitive processes linked to the level of automatism handled through the different conditions by the controllers. Specifically, it was considered the bunch of brain features linked to cognitive processes such as information processing, attention, working memory, and decision making, without considering motor brain features. Such features (e.g. sensory premotor cortex) were not considered for not differentiating the SRK behaviours on the base of different amount of movements (hands and/or feet) during the execution of the ATC operations.

Besides, to maintain the realism of an operational air-traffic setting, the ATM scenario was created and validated by ATCO and HF experts. Also, to investigate if the selected brain features were able to measure and quantify the three levels of control in realistic conditions, the SRK events were inserted into the ATM scenario with different complexity levels, where the task difficulty (or mental workload) varied over time to simulate realistic air-traffic situations.

The brain features measured and analysed for the SRK discrimination were:

1. The **frontal theta EEG rhythm**, which is correlated to decision–making processes and working memory, and it is also directly connected to the amount of information and stimuli to elaborate. Indeed, it was demonstrated that the more complex is the task, the higher is the theta synchronization over frontal brain areas.
2. The **parietal theta EEG rhythm**, which is linked to procedural memory. Indeed, it was demonstrated that the more sustained is the memory consolidation, the higher is the theta synchronization over parietal brain areas.
3. The **frontal alpha EEG rhythm**, which is connected to the attentional level. Indeed, it was demonstrated that the higher is the attention, the more is the alpha desynchronization over frontal brain areas.

The PSD analysis of these EEG rhythms over the SRK conditions confirmed that frontal and parietal theta and frontal alpha brain features varied significantly along the three levels of cognitive control, as shown in Figures 11, 12 and 13.

As expected, indeed, the frontal theta PSD increased with the complexity of the task, especially in the knowledge condition than in the skill condition. On the other hand, the parietal theta PSD, linked to the memory consolidation, increased more during procedural or planning activities, such as knowledge and rule conditions, than during automatic activities, such as skill events. In the same way, the frontal alpha PSD, linked to the attentional level, desynchronised more during automatic actions (such as skill events) than during activities where the access to Knowledge System (KS) was required, such as rule and knowledge conditions.

It is worth noting that during the PSDs analysis it was not possible to discriminate all the SRK levels, but only the K, R conditions from the S ones, and not the K from the R ones.

On the contrary, by using a machine-learning approach, it was possible to discriminate significantly all the three levels of cognitive control of behaviour.

Besides, the considered EEG features allowed to highlight the differences between the groups of Experts and Students ATCOs in terms of expertise, as shown in Figures 14-18. In this regard, the Experts ATCO showed higher memory consolidation and both lower attentional request and demand on executive controls than the ATCO Students. Such brain features were then used for the calibration of the asSWLDA classification algorithm, to investigate the possibility to discriminate the three levels of cognitive control during the execution of the realistic ATM scenario.

The results confirmed that the asSWLDA was able to discriminate significantly the SRK conditions, as all the measured AUC distributions were significantly higher ($p < 0.05$) than the chance level (Figure 14). Additionally, the analysis on the amount of brain features selected by the asSWLDA for each group demonstrated how the ATCO Students showed higher frontal brain activation than the ATCO Experts in dealing with the same SRK events, as shown in Figures 19 and 20. Thus, it is possible to conclude that the differences observed between the two groups reflect the higher information processing and working memory activity for the Students with respect to the Experts, due to the different degree of expertise.

A limitation of the study can be noticed because of the high realism of the ATM scenario. In fact, it was not possible to create “pure” SRK events, but they were performed in combination with the ATC operations.

Furthermore, to investigate the possibility to measure and quantify the three levels of control in realistic settings, the SRK events were inserted by ATCOs and HF experts into an ATM scenario with different levels of complexity, where the task difficulty (or mental workload) continuously changed over time to simulate realistic air-traffic conditions. So, it was tested whether it was possible to discriminate the SRK conditions when the difficulty of the faced events changed.

As a result, in the next steps, further investigations in more controlled experimental settings should be performed to simulate more appropriate “pure” skill, rule and knowledge events during the task. In this way, the realism of the simulation would decrease, but probably confirm the promising findings of this research.

5. CONCLUSIONS

Several HF studies mentioned the different information processing levels of Skill, Rule, and Knowledge, but no mention is done in the existing literature regarding neurophysiological features. The aim of this study was to address this gap trying to map the neurophysiology of the SRK framework by identifying EEG indicators that could potentially be used to discriminate the three levels of behaviour in ATM domain.

This research demonstrated that it is possible to assess, with a high reliability, the ATCOs' levels of cognitive control of behaviour during the execution of a realistic ATM scenario throughout specific brain features [134], [135]. Frontal and parietal theta and frontal alpha were selected to characterize the SRK levels of performance, in terms of cognitive processes and level of automatism involved, reducing the probable influence due to the motor activity.

From the results, it is possible to observe that:

a) the proposed neurometric (frontal and parietal theta, and frontal alpha EEG rhythms) could be valid metrics for the investigation and objective analysis of the operator's cognitive control of behaviour (SRK);

b) the machine-learning algorithm asSWLDA is able to discriminate significantly the three levels of behaviour for both the ATCOs groups (Experts and Students);

c) the methodology proposed in the research could be applied to the evaluation of the level of expertise between groups in real operative environments (e.g. Experts vs Students ATCOs).

Furthermore, others promising applications of the proposed method could be potentially the following:

a) as a Human Factors tool for the design of new solutions, for example triggering adaptive automations depending on the operator's current level of cognitive control;
b) as a Training tool for tracking the level of learning and expertise gained by the operator;
c) as a Monitoring tool to be used during operations (e.g. crew monitoring on a/c or ATC rooms).

Besides, it could provide objective information about the prediction of possible operators' failures in achieving his/her goals. This is important especially in Safety and Human Factors domains where improving the operators' performance or avoiding error-prone situations are critical issues.

As a result, the use of this methodology could represent a promising step forward into the analysis and knowledge of Human Cognition and Behaviour.

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7. ACKNOWLEDGEMENTS

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