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A Cognitive Predictive Model of Air Traffic Controller's Mental States

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Abstract

This paper presents the development and implementation of a psychological model aimed at predicting the mental states of Air Traffic Controllers (ATCOs) within an Exploratory research project, entitled CODA (The Controller Adaptative Digital Systems Assistant), within the SESAR 3 Joint Undertaking and European Union's Horizon Europe research and innovation programme. The proposed model aims to advance human–machine collaboration in air traffic management by enabling the precise prediction of critical operator cognitive and affective states, including mental workload, fatigue, stress, and attentional engagement. By formally integrating core cognitive processes—namely perception, comprehension, and decision-making—within its architecture, the model provides a principled framework for the continuous monitoring and real-time adaptation of support systems. Such adaptive capabilities are intended to optimize the allocation of assistance provided by artificial agents, thereby strengthening human–system coordination and contributing to enhanced operational safety and efficiency within the complex and highly dynamic environment of air traffic control. To estimate the parameters of the model, several air traffic simulations were conducted with expert controllers. In these simulations changes to traffic situations were introduced. Those changes could affect the controllers' mental states. The results of these changes were observed in the measured verbal and psychophysiological dependent variables. This paper presents results that partially validate the initial parameters of the models. These results will contribute to a future improvement of the model by refining the parameters of the proposed formulas for calculating mental workload, fatigue, stress, and vigilance in the air traffic control task.

Keywords: air-traffic controller; mental states; predictive model; artificial intelligence support tool

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1. Introduction

Artificial intelligence can improve the performance of complex tasks by automating processes and optimizing decision-making through the analysis of large volumes of data. Intelligent systems can offer real-time assistance—such as recommendations, error detection, and predictive analytics—that increases accuracy and efficiency, reducing the margin of error and improving the organization's overall results. Furthermore, AI can also significantly contribute to employee satisfaction by reducing fatigue and stress. The task performed by air traffic controllers is one example of a complex and dynamic task in which artificial intelligence can help improve both performance and satisfaction by facilitating decision-making and optimizing execution.

Based on this assumption, several research institutions have been developing are AI systems to help air traffic controllers perform their control tasks. One of these systems is being developed in an Exploratory research project, entitled CODA (The Controller Adaptative Digital Systems Assistant), within the SESAR 3 Joint Undertaking and European Union's Horizon Europe research and innovation programme. The CODA solution seeks to improve the efficiency, capacity, and safety of

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Air Traffic Management (ATM) through enhanced human–AI collaboration. Within this context, a system has been developed up to Technological Readiness Level 2 (TRL2) to support the execution of collaborative tasks by hybrid human–machine teams. Task allocation is dynamically managed according to adaptive automation principles, including the selective activation of Digital Assistants. A schematic overview of this approach is presented in Figure 1.

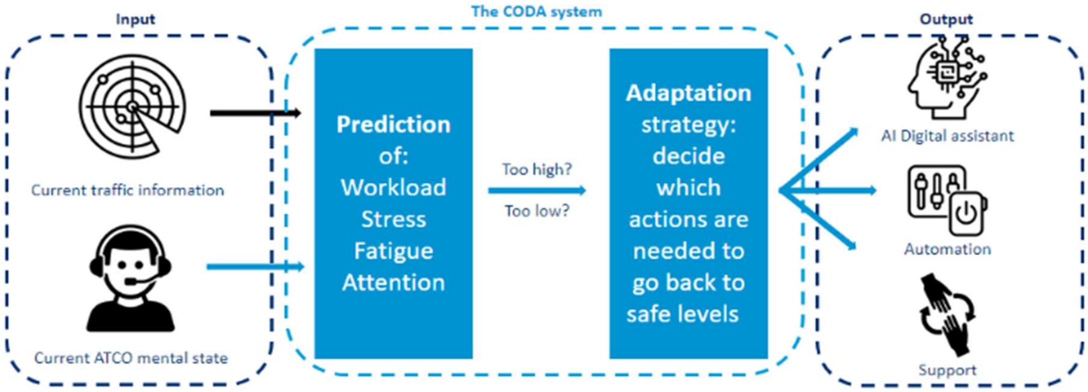

Figure 1. Summary of the CODA concept (blue elements are the ones addressed by the project).

Specifically, the system is based on several components:

- Current mental state assessment: assess the current status of the operator (e.g. level of workload, stress and other relevant human factors).
- Tasks prediction: A task predictor has been developed using current traffic data to foresee the future tasks that the operator will need to perform in the future.
- Mental states prediction: calculate the impact of predicted tasks in terms of cognitive complexity, time on task and stressors.
- System adaptation: With the information gathered by the previous models, the system predicts the future mental state of the operator and will act accordingly.

In order to predict the mental states of the controller, the CODA project has created to a Psychological mental prediction model. This mental prediction model was created within CODA to provide information regarding the controllers' workload, stress, fatigue, and decrements in vigilance. The mental model has been modelled using psychological theories adapted to the En-Route executive controller role.

Task performance in domains such as air traffic control can be understood as the emergent outcome of a Joint Cognitive System integrating human cognitive processes, technological artifacts, and the organizational context in which activity takes place (Hollnagel & Woods, 1983; Hutchins, 1996). Within this socio-technical system, cognitive activity is distributed across individuals and artifacts and is shaped by organizational constraints and procedures. In this context, interaction between operators and artifacts constitutes a structured process. According to Venda, Trybus, and Venda (2000), this process can be described in terms of a set of components and stages:

- Environmental stimuli are presented to individuals, serving as external inputs to their cognitive processes.
- Perceptual processes convert these external inputs into internal representations for further cognitive processing.
- Cognitive processes generate external outputs, which impact the environment. The individual's external outputs, manifested through their behaviour, alter the environment, which possesses its own internal dynamics leading to autonomous changes.
- Individuals observe the changes in the environment and subsequently adjust their actions based on these changes.

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The recursive nature of this process is a defining characteristic of the system and is explicitly captured in the fourth component. Human behaviour alters the environment, thereby initiating a new interaction cycle. The environment may subsequently evolve autonomously, and these changes in turn provide new inputs to human cognitive processes. Through this continuous feedback loop, the recursive dynamics of the human–environment system are sustained.

In traditional accounts of this recursive process, artifacts and the environment were assumed to respond passively to human behaviour, lacking the capability to interpret such behaviour for adaptive purposes. The integration of Artificial Intelligence challenges this assumption by enabling artifacts and environmental systems to infer aspects of human cognitive and behavioural states and to adjust their characteristics accordingly (Scerbo, 2020). Through the analysis of behavioural and cognitive indicators during interaction, artificial systems can dynamically modify system functions to support more effective human–system performance. In practice, such adaptation typically involves adjustments in the level of automation based on both current and anticipated operator states. This capability underlies the concept of *adaptive automation*, a central paradigm in research on human–automation interaction (Hancock, Jagacinski, Parasuraman, Wickens, Wilson, & Kaber, 2013).

Effective adaptive automation requires that the components of a Joint Cognitive System maintain a degree of mutual modelling, enabling the estimation and prediction of each other's states and future behaviours (Rizzolatti & Craighero, 2004). This requirement parallels the mechanisms that support coordination in human–human interaction, where successful collaboration depends on the ability to perceive and interpret others' actions in order to infer their intentions and goals. Evidence from cognitive neuroscience suggests that this capability is supported by the *Action Observation Network*, also referred to as the *Mirror Neuron System*. This distributed neural network, encompassing occipital, temporal, and parietal regions as well as parts of the frontal cortex, supports the perception and interpretation of others' actions during social interaction (Rizzolatti & Craighero, 2004).

For artifacts and environmental systems to interpret human behaviour, they must first capture observable actions and the parameters that characterise those actions. From these data, behavioural patterns can be inferred, enabling the prediction of future actions. This principle has been examined in studies of human–robot collaboration, such as the work of Busch, Grizou, Lopes, and Stulp (2017), which investigated factors affecting the interpretability of behaviour among agents engaged in joint activity. Their findings suggest that effective collaboration between human and automated agents requires human behaviour to be *legible* to the automated agent. Legibility refers to the extent to which an observer can rapidly and accurately infer an agent's intentions from its actions. Achieving this capability requires artifacts and environmental systems to maintain an internal model of the human operator, allowing them to interpret and anticipate human behaviour.

Research suggests that individuals interpret and predict the behaviour of artifacts and environmental systems on the basis of mental models of their structure and function stored in memory (Moray, 1999). In a similar manner, artifacts and environmental systems require an internal model of the human operator in order to infer underlying mental states and interpret observed behaviour.

Psychological models have traditionally sought to explain human behaviour and mental states, often assuming that explanatory adequacy would also confer predictive capability. Under this assumption, models capable of accounting for past or current behaviour were expected to generalise to the prediction of future states. However, decades of psychological research have shown that this assumption frequently does not hold. Many models developed using statistical approaches focused primarily on fitting observed data exhibit limited predictive power when applied to future mental states or behaviour. This limitation arises largely from an emphasis on explanation and data fitting rather than on predictive performance. The emergence of machine learning approaches has begun to shift this emphasis, placing prediction at the centre of model development. In this framework, models are designed to generalise to previously unseen data, even when the psychological mechanisms underlying their predictions are not fully specified.

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Consequently, there is a growing call within the research community for psychological models that combine explanatory and predictive capabilities (Yarkoni & Westfall, 2019). Such models are particularly important for supporting effective recursive interaction within Joint Cognitive Systems. For adaptive interaction to function effectively, artifacts must not only interpret operators' current behaviour and mental states but also anticipate their near-future states. In the context of air traffic control, a psychological model of air traffic controllers (ATCOs) that integrates explanation and prediction would enable both human operators and artificial systems to operate more effectively within the collaborative cognitive system of ATM.

By providing a representation of how ATCOs perceive information, make decisions, and respond to changes in the operational environment, such a model would allow artificial systems to interpret controller behaviour and mental states and to support adaptive automation aligned with operator needs. At the same time, it would facilitate more transparent and predictable system behaviour, supporting controllers' situational awareness and decision making. This mutual predictability between human and artificial agents is essential in the dynamic and safety-critical environment of air traffic control, where effective performance depends on the continuous coordination of human and automated components.

This paper presents a predictive model of key mental states in air traffic controllers (ATCOs)—including workload, fatigue, stress, and vigilance—developed within the framework of the CODA project. The paper first outlines the theoretical foundations of the model and then describes its main components. Finally, results from an air traffic control simulation are presented, in which the model's predictions were calibrated and evaluated.

2. Theoretical Background

The predictive psychological models developed in CODA and described in this paper is composed by two components:

1. Models of the **structure** of the cognitive system, which aim to explain the organisation and components of the cognitive processes involved in human behaviour (i.e. Histon and Hansman,2008)
2. Models of the **energy** this cognitive structure requires to operate effectively (i.e., Hockey, Coles, and Gaillard, 1986).

These two categories provide complementary perspectives for understanding and predicting human behaviour in various contexts, including in tasks such as air traffic control.

3. ATCo Cognitive Structure

To effectively model the cognitive structure of an air traffic controller, it would be beneficial to distinguish between cognitive processes and the phases of cognitive information processing (Histon and Hansman, 2008):

1. **Cognitive Processes:** These are the mental operations involved in perceiving, interpreting, storing, retrieving, and using information. Examples include attention, perception, memory, decision-making, problem-solving, and action planning.
2. **Phases of Cognitive Processing:** These represent the sequential stages through which the cognitive system processes information. These phases typically include perceiving, comprehending, projecting the system's future state, decision-making, and acting.

The initial stage of cognitive processing entails the perception of elements present within the operational environment. Air Traffic Controllers (ATCos) must acquire all relevant information pertaining to traffic and surrounding conditions, whether directly through sensory channels or via the instrumentation available at the control position. This perceptual phase is underpinned by sensory mechanisms that transduce physical stimuli into neural signals, alongside perceptual processes that assign meaning to the information received.

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Subsequently, having acquired environmental data, the ATCo must establish a coherent understanding of the behaviour of the elements within the operational environment and the interrelationships among them. The comprehension of this environment is contingent upon memory processes, whereby mental models are constructed in working memory through the integration of newly perceived information with knowledge retrieved from long-term memory.

The air traffic control (ATC) environment is inherently dynamic, characterised by continuous variability in traffic, meteorological conditions, wind shear, and airspace restrictions. Crucially, irrespective of the controller's actions, aircraft continue to operate in accordance with pilot inputs and prevailing environmental factors, such as wind direction and speed, and aircraft weight. Consequently, a momentary understanding of the traffic situation is insufficient for the effective execution of control tasks. It is equally imperative that controllers project the current state of elements forward in time, anticipating the future configuration of the traffic situation. This projection is grounded in the mental model held in working memory (Cañas, Antolí, & Quesada, 2001).

The three aforementioned phases (perception, comprehension, and projection) provide the cognitive foundation necessary for the subsequent processing stage of decision-making (Endsley, 1995). Without the successful completion of these phases, the safe and effective management of air traffic control operations cannot be achieved.

Upon encountering a potential conflict, ATCos are required to assess whether intervention is necessary. In the event that they determine intervention to be appropriate, they must select the most suitable operational mode, evaluated according to three key criteria: effectiveness, defined as the capacity to resolve the conflict optimally; efficiency, understood as the minimisation of system costs and mental workload; and safety. Once a decision has been reached, controllers are expected to act accordingly. Finally, motor processes bear responsibility for planning and generating responses to the environment, informed by the decisions produced through the preceding cognitive processes as well as by the environmental information available at the time.

4. Mental Resources

Cognitive processing entails a necessary expenditure of energy, insofar as the human body functions as an energetic system that requires a sustained energy supply to operate efficiently. Effort can be understood as the subjective intensification of mental and/or physical activity oriented towards the attainment of a specific goal. This conceptualisation may be refined by asserting that effort serves as a mediating variable between, on the one hand, the objective demands of a given task and the mental processing capacity available to the individual, and, on the other, the effectiveness with which the relevant mental operations are carried out, as evidenced by task performance outcomes. Three constituent components can thus be identified within this refined framework: (a) the nature and characteristics of the task to be performed; (b) the individual's mental capacity to undertake it; and (c) the actual quality and manner of task execution. A thorough analysis of these three components necessitates recourse to the concept of Mental Resources, which provides the operational basis for defining effort and for understanding its broader function within the context of human work.

The concept of mental resources has its origins in longstanding concerns regarding the role of human effort in task performance and occupational health. These concerns are rooted in two ideas that have developed within Western philosophical tradition from the Renaissance to the present: Mechanism and the psychophysiological conception of the human being as an Energetic Mechanism. Mechanism constitutes a philosophical concept that attained considerable prominence in Western thought between the 14th and 19th centuries, emerging as a central tenet of the broader intellectual movement known as Materialism (Rabinbach, 1992).

In order to fully understand the mechanisms by which the human neurocognitive system regulates and manages energy, it is necessary to differentiate between three distinct types of mental resources.

- **Demanded Resources**: the amount of mental resources required to perform a task.

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- **Available Resources**: the amount of resources an individual has available at any given moment to meet this demand.
- **Applied Resources or Effort**: the portion of the available resources allocated to address the demanded resources.

4.1. Demanded Resources

Demanded resources are those mental resources that a given task requires, and their magnitude is directly contingent upon task complexity. Complexity has long been conceptualised as an inherent characteristic of environmental structure, with the prevailing assumption that it resides within the stimulus itself — a perspective that underpins the notion of "Taskload." From this standpoint, parameters such as the number of elements present in the environment (e.g., the volume of aircraft in air traffic control operations) and the nature of their interactions are regarded as straightforward indicators of complexity: as the number of elements and interactions increases, so too does the level of complexity. This traditional view is predicated on the assumption that complexity can be objectively quantified within the stimulus, in line with what is referred to as the "Systems Engineering Approach." Guided by this framework, sustained efforts have been made to develop algorithms capable of calculating complexity on the basis of environmental parameters (Walker, Stanton, Salmon, Jenkins, & Rafferty, 2010). Nevertheless, following a prolonged series of largely unsuccessful attempts to devise reliable measurement algorithms, there is now broad consensus that complexity should be reconceptualised as a property of the cognitive processing of environmental structure, rather than of the structure itself. This shift has prompted a redefinition of complexity from the standpoint of the controller's cognitive system. Introducing the cognitive dimension into the concept implies that the complexity of a stimulus is determined not by its objective properties, but by the extent to which it challenges the human cognitive system to process it; in other words, complexity is defined by cognitive processing of the stimulus. Consequently, Human Factors researchers have increasingly sought to define complexity within the Person-Machine System perspective (Walker et al., 2010) — a framework that conceives of complexity as an emergent property of the interaction between humans and the broader system (including machines, organisational structures, and associated components) in the context of collaborative activities such as air traffic control. In their systematic review of how complexity has been theorised in professional journals over recent decades, Walker et al. (2010) identified three defining factors: multiplicity, dynamism, and uncertainty. Together, these factors elucidate the relationship between complexity and human-system interaction, and provide a valuable basis for determining the mental resources demanded by a task as a function of the complexity of that interaction.

Considering the foregoing, a model such as that advanced by Histon and Hansman (2008) may offer a valuable framework for understanding what the concept of "complexity" encompasses within the field of Human Factors. The interest in complexity as a central concept within Air Traffic Management (ATM) is warranted by the broadly accepted premise that the effectiveness, efficiency, and safety of the activities carried out by individuals responsible for organising air traffic are substantially conditioned by the complexity of their operational environment. This recognition has prompted considerable investment of effort in defining and, above all, in operationalising the measurement of complexity within ATM contexts. The insights derived from such assessments, undertaken at specific points in time, may subsequently inform decisions regarding airspace restructuring, the deployment of automated support tools, or the design of training programmes tailored to conditions of varying complexity.

4.2. Available Resources

For the human mental system to satisfy the resource demands of a given task, it must make available a sufficient quantity of mental resources. This process of resource provision has been conceptualised in different ways across theoretical frameworks: within the classical paradigm of the

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human energetic motor, it is understood as an energy supply, whereas within psychophysiology it is described in terms of an activation process. In both cases, this phenomenon is referred to as effort.

Effort can be defined as the allocation of available mental resources relative to the demands that a task places upon the individual. The magnitude of this allocation — which is, in essence, what effort consists of — is principally determined by the resources available at any given moment, though it is also shaped by the goals the individual is seeking to achieve and the motivation underpinning that pursuit. Crucially, however, human responses to task demands are not linear; individuals do not simply deploy available resources in direct proportion to what a task requires. Instead, they engage in active resource management, calibrating their allocation in accordance with task complexity, the objectives at hand, and the level of effort they are willing to expend. Effective resource management thus necessitates careful consideration of both the quantity of available resources and their temporal dynamics, as well as an understanding of how these factors are conditioned by the relationship between the resources demanded by the task and those available to the individual.

The Compensatory Control model proposed by Hockey in 1987 offers insights into how the nervous system adapts to task demands, highlighting the importance of resource management. Additionally, the ATCo's actions are planned to achieve control task objectives, influenced by mental resource management as well as strategies developed through training and experience. Therefore, a comprehensive model should integrate mental resource management with action planning to accurately explain and predict performance in air traffic control tasks.

Hockey (1997) posits that behaviour is fundamentally motivated by the desire or necessity to achieve goals, a process that inherently demands the exertion of effort. Given that each goal carries a specific value and requires a particular expenditure of effort, it becomes possible to subject each pursued objective to a cost-benefit analysis, weighing the value of the goal against the effort required to attain it.

Within Hockey's model, task performance is conceived as a process of goal selection from among multiple available options, each of which carries specific demands in terms of energy expenditure. When the effort required to achieve a given goal remains within the bounds of the individual's available energy reserves, all resources are allocated accordingly. When, however, the demands of the task exceed available reserves, the individual is faced with the need to re-evaluate the relative worth of the goal in question (determining either whether its pursuit remains justified or whether the investment of effort would be more appropriately redirected towards an alternative objective).

The designation of this framework as a "motivational control" model reflects its central emphasis on not merely the effort or energy that a goal demands, but on the broader question of whether such effort is warranted in light of the anticipated benefits. According to the model, a goal is selected from among competing alternatives, and the actions performed in pursuit of that goal necessitate specific allocations of mental resources. Two evaluative mechanisms operate within this process: an "Action Monitor," which appraises the effectiveness of the actions undertaken, and an "Effort Monitor," which determines whether the effort being invested is sufficient for goal attainment and mobilises additional energy when required. In circumstances where the effort demanded proves excessive, the Effort Monitor may initiate a reassessment and propose the adoption of an alternative goal. This ongoing evaluative process is underpinned by the concept of mental workload, which captures the dynamic relationship between the cognitive complexity of task demands and the mental resources available to the individual at any given moment.

Within Hockey's framework, fatigue is conceptualised as a "subjective" sensation produced by the Effort Monitor, serving as a signal that the effort required is approaching excessive levels. The experience of subjective fatigue thus functions as an early warning that available resources risk becoming depleted, though it does not in itself indicate that those resources have already been fully exhausted. A notable feature of the model is its explicit differentiation between subjective experiences (including fatigue and mental load) and the physiological processes that underlie them, as well as the distinct consequences each may have for task performance.

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As an illustrative example, the model proposes that an individual may experience fatigue whilst driving, even in the absence of any observable deterioration in performance. Under such circumstances, fatigue operates as a warning mechanism, signaling that the effort being invested is beginning to surpass the resources available, and indicating that a period of rest may be warranted. In this sense, fatigue serves to trigger a reassessment of the cost-benefit ratio of the goal being pursued, prompting the individual to weigh whether continued investment of effort remains justified or whether it would be more appropriate to redirect resources towards an alternative objective.

At the neurological level, the compensatory control mechanism is underpinned by two key brain structures: the prefrontal cortex (PFC) and the anterior cingulate cortex (ACC) (Otto, 2013; Ishii, Tanaka, & Watanabe, 2014). The PFC assumes responsibility for goal setting and for maintaining the sustained neural activity required to pursue the chosen goal. Empirical research has demonstrated that neuronal activity within the PFC tends to decline progressively over the course of extended task performance. This goal management function encompasses both the selective focusing of neural activation on task-relevant stimuli and the active suppression of irrelevant distractors. The ACC, in contrast, serves a monitoring and evaluative role, appraising the execution of the task and assessing the status of available mental resources relative to the goal being pursued and the motivational context in which it is embedded, before relaying the outcomes of this cost-benefit analysis to the PFC.

5. Operational Modes

The development of a psychologically valid computational model for complex operational tasks such as air traffic control requires the recognition that an individual's responses cannot be treated as discrete, independent units susceptible to isolated analysis. On the contrary, responses are organised into coherent structures that constitute integral components of both reactive and, more significantly, proactive coping strategies directed at managing environmental events. By the same token, environmental events are not independent of one another but are inherently interrelated. A pertinent illustration of this interdependence is the approach of multiple aircraft to an airport, which demands the coordinated assignment and management of altitudes and headings, necessarily accounting for the collective ordering and spatial disposition of all aircraft within the relevant airspace.

This perspective aligns with Sperandio's (1978) classic article, which proposed that to measure a controller's workload, it is essential to analyse their response strategies using what he termed "Operational Mode" (OM) as the unit of analysis. Sperandio demonstrated that French controllers he studied employed a strategy of planning aircraft contacts on a plane-to-plane basis. However, when mental workload exceeded manageable levels, they switched to a fixed contact strategy for all aircraft. Sperandio interpreted this shift as **a means of minimizing cognitive demand by reducing the involvement of cognitive channels**, thereby prioritizing safety over passenger comfort, which requires more complex cognitive processing.

Extending Sperandio's (1978) foundational proposal, an Operational Mode (OM) can be defined as a structured sequence of actions directed towards the achievement of a specific objective. Human task performance characteristically involves a range of alternative action sequences (or behavioural strategies) through which a given goal may be pursued, and an OM constitutes one such alternative. The systematic study of OMs within the domain of air traffic controller work was inaugurated by Sperandio (1978), whose research demonstrated that controllers strategically adopt different OMs in accordance with fluctuating levels of mental load. This conceptual framework was subsequently developed by Histon and Hansman (2008), who, in the course of their doctoral research, identified four distinct OMs through which controllers respond to the varying cognitive demands characteristic of different air traffic situations.

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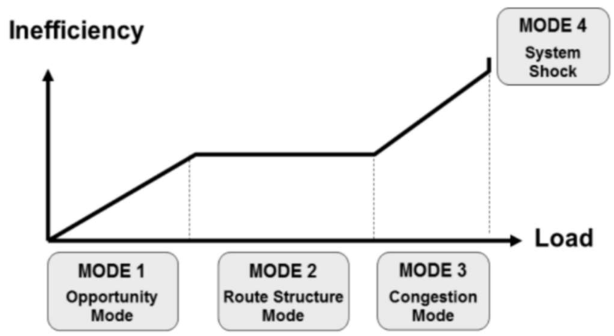

Figure 2. OMs found by Histon (2008).

- Mode 1. Opportunistic Mode: Under conditions of low traffic volume, where individual aircraft tracking is not operationally necessary, the controller retains ample mental resources to monitor each aircraft on an individual basis and to conduct systematic pairwise comparisons between them.
- Mode 2. Route Structure Mode: As traffic volume increases, controllers begin to rely on memory-based abstractions of traffic situations. These abstractions encode standardised routes that serve as cognitive reference points, enabling controllers to classify aircraft mentally as either adhering to or departing from established standard flows. By drawing on these cognitive structures, controllers are able to manage a larger number of aircraft without incurring a commensurate increase in cognitive load, albeit at the potential cost of a marginal reduction in the efficiency of individual aircraft management.
- Mode 3. Congestion Mode: With continued growth in the number of aircraft, controllers find it increasingly difficult to apply the route structures stored in memory. In response, it becomes necessary to divert certain aircraft from standard flows onto less efficient routes, thereby alleviating demand on those flows and enabling the controller to continue utilising simplified approximations of the standard structural frameworks.
- Mode 4. System Shock: Although relatively infrequent in occurrence, sudden and unforeseen changes in traffic conditions or environmental factors may necessitate the urgent formulation of contingency plans. In such emergency situations, controllers may be compelled to revert to Opportunistic Mode, reverting to pairwise comparisons as the primary means of managing the altered traffic environment.

When controllers perceive that the level of complexity in their operational environment is approaching their internal tolerance thresholds, they are anticipated to shift towards simpler and less cognitively demanding modes of operation (Figure 3).

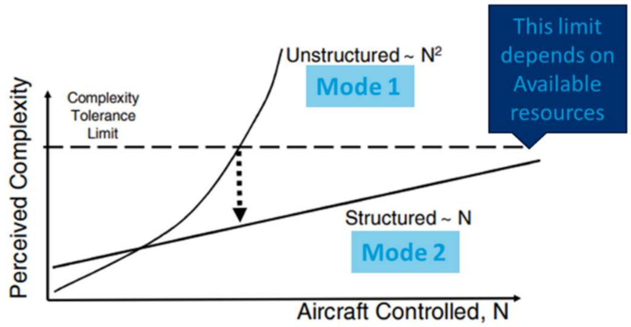

Figure 3. Shifts to alternative operational modes allow controllers to maintain perceived complexity below a notional tolerance limit.

The central argument put forward by Histon and Hansman, grounded in and extending Sperandio's original proposal, holds that controllers transition between operational modes as a function of the mental states engendered by the cognitive complexity of both the traffic situation and the broader operational environment, as well as the mental resources available at any given moment. By adaptively modulating their operational modes in this manner, controllers are able to regulate mental load, fatigue, and stress, thereby ensuring that performance in the control task is both optimised and sustained within the bounds of operational safety.

This thesis is closely aligned with Hockey's Compensatory Control Model of human performance, the core tenets of which provide a complementary theoretical foundation for the proposed framework. Figure 4 illustrates the relationship between the Compensatory Control Model and the Operational Modes framework, presenting an integrated theoretical construct that brings together both models. The Compensatory Control Model holds that individuals adaptively modify their behaviour in response to fluctuations in task demands and available resources, whilst the OM framework proposes that operators select and continuously adapt their operational strategies in accordance with the demands of the current situation and the resources available to them at any given moment.

The proposed model seeks to integrate the Compensatory Control Model with the Operational Modes framework in order to provide a comprehensive account of how individuals manage tasks and allocate resources. The control process is set in motion by the occurrence of either an internal or external stimulus, whereupon the operator selects the most appropriate Operational Mode (OM) in light of task demands, the availability of resources, and accumulated prior experience. An ensuing assessment establishes the resource requirements associated with the selected OM and compares these against the resources presently available to the operator. In the event that a resource deficit is identified, the system initiates efforts to augment the available resource pool.

Throughout this process, the system continuously monitors the operator's effort to sustain the selected OM within the constraints imposed by available resources, whilst concurrently pursuing the highest attainable level of performance. When performance begins to deteriorate or resource depletion reaches a critical threshold, a new OM is selected and the entire cycle is set in motion once again. It is the interplay of three foundational principles (adaptive behaviour, efficient resource management, and the ongoing optimisation of performance) that lies at the conceptual core of this integrated model.

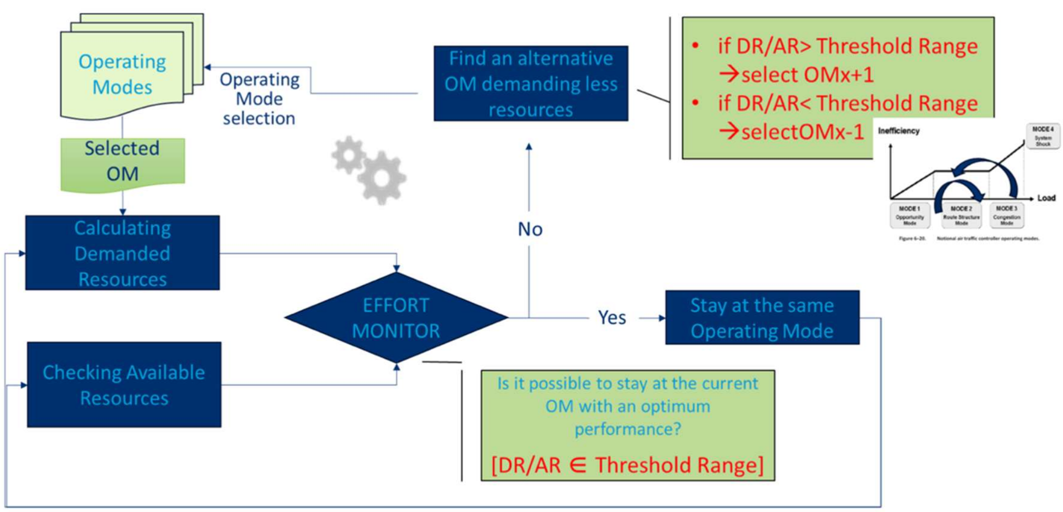

Figure 4. The Compensatory Control Model (After Hockey, 1997).

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6. Mental States models based on the Available Resources Model

Mental states contingent upon mental resources are not amenable to direct observation; they can only be accessed indirectly, through their effects on task performance, measurable psychophysiological parameters, or the phenomenological verbal expressions of the individuals who experience them. At the same time, fluctuations in mental states are brought about by external factors that are themselves subject to observation and measurement. However, mental states cannot be directly observed but can only be inferred from the relationships that obtain between the factors that produce them and their observable effects. It is therefore of critical importance to avoid conflating mental states with their antecedent causes, the factors that modulate them, or the observable effects through which they manifest. The accurate characterisation of mental states must always proceed by way of the systematic observation and measurement of these causes and effects, in conjunction with the inferential identification of the underlying brain mechanisms through which causes are translated into effects.

From the perspective of causal factors, it is important to distinguish between mental states that arise as a consequence of task performance — such as those associated with work — and those that result from neurological pathologies, such as multiple sclerosis. Within CODA, attention is directed exclusively towards mental states related to task performance, specifically within the context of air traffic control. Although research on neuropathologies affecting mental states can yield valuable insights into the neuropsychological mechanisms underlying these states (DeLuca, 2005), the primary concern of the present work remains task-related mental states.

When considered from the vantage point of their observable effects, mental states manifest across three distinct dimensions. The first and most immediate of these concerns task performance: mental states contingent upon available resources exert a tangible influence on how tasks are executed, with conditions such as fatigue or stress having well-documented consequences for performance outcomes including, for example, an increase in the frequency of errors. The second dimension encompasses psychophysiological parameters: a range of measurable physiological indicators fluctuate in systematic correspondence with underlying mental states and can be reliably assessed through appropriate instrumentation; research has demonstrated, notably, that cortical electrical activity and eye movement parameters serve as sensitive indices of specific mental states. The third dimension involves self-report: soliciting verbal accounts from individuals regarding their subjective experience can provide a direct and ecologically valid window into their mental state — asking a person to quantify their perceived level of fatigue at a given moment during task performance, for instance, affords an immediate and personally grounded indication of their current psychological condition.

Within the CODA framework, the mental states of primary concern are mental workload, fatigue, stress, and sustained attention — each of which is fundamentally conditioned by the management of available cognitive resources and by the manner in which those resources fluctuate over time. Beyond these core mental states, the framework also addresses the mental states associated with resource availability in the context of a specific subtask embedded within the broader air traffic control task: the vigilance task. This subtask requires the ATCo to sustain a heightened level of attentional engagement over a prescribed period in order to detect the occurrence of a specified event — a demand that places the cognitive process of Sustained Attention at the very centre of successful task execution.

6.1. Mental Workload

Mental workload is defined as the relationship between the resources demanded by a task and the operator's available resources (Young, Brookhuis, Wickens, & Hancock, 2015). When task demands exceed an individual's available mental resources, the result is mental overload; conversely, when demands fall short of available resources, mental underload ensues. When demanded and

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available resources are in equilibrium, no issue of mental load arises. Mental load is therefore fundamentally contingent upon the balance between demanded and available resources.

As established above, resource demands can be operationalised in terms of cognitive complexity, which is defined as the cognitive difficulty entailed in managing a given air traffic situation. This construct is associated both with the characteristics of the relevant stimuli — encompassing traffic conditions and environmental factors — and with the complexity of the cognitive functions required to perceive, comprehend, project, make decisions, and execute actions in response to those stimuli. In collaboration with the Universidad de Granada (UGR) and its principal stakeholder, the Spanish Air Navigation Service Provider ENAIRE, CRIDA has developed a computerised predictive model of ATCo cognitive complexity and, consequently, of ATCo mental workload (López, Rodríguez, Zheng, & Zheng, 2019; Ibáñez, Travieso, Navia, Montes, Jacobs, & López, 2023). This model draws upon the working mental model advanced by Histon and Hansman (2008), which is founded on cognitive abstractions designed to represent the essential characteristics of a mental model in a more cognitively compact form — one that remains manageable within the inherent constraints of human memory capacity and cognitive processing limitations. Histon and Hansman identify three categories of mental abstraction employed by ATCos to mitigate cognitive complexity: standard flows, critical points, and grouping. On the basis of this framework, it is hypothesised that traffic and airspace features which fail to support these abstractions function as primary sources of cognitive complexity.

- **Standard Flow Abstractions** are defined as recurring patterns of aircraft that share common lateral paths and are typically arranged in an in-trail configuration relative to one another. By providing a structured cognitive representation of traffic organisation, these abstractions assist controllers in managing their operational tasks, reduce the cognitive demands associated with maintaining situational awareness, and support the critical decision-making processes through which a current operational plan is developed.
- **Critical Point Abstractions** represent generalisations of high-priority regions within a given sector — most commonly locations at which controllers have learned to anticipate potential conflicts or other sources of recurring operational difficulty, such as the overshooting of a turn on an established airway. These abstractions enhance perceptual efficiency by focusing the controller's attentional scan on those areas of the sector where problems are most likely to occur, whilst concurrently supporting the cognitive processes of projection, monitoring, evaluation, and planning.
- **Grouping Abstractions** function by consolidating constituent elements of a traffic situation (primarily individual aircraft, though also potentially including sets of meteorological objects) into coherent units within the working mental model. In doing so, they assist controllers in managing their tasks, alleviate the cognitive burden associated with maintaining situational awareness, and facilitate the key decision-making processes that lead to the formulation of a current operational plan.

The other component of mental load, the available resources, will depend on many factors, among which the time spent on the task stands out.

6.2. Fatigue

According to the European Commission (Regulation 2017/373), fatigue is defined as a physiological state characterised by diminished physical or mental performance capacity, arising from factors such as sleep loss, prolonged wakefulness, circadian phase disruption, or the demands of mental or physical workload, or a combination thereof. In this state, an individual's capacity to sustain alertness and carry out tasks safely may be significantly compromised.

This definition is not without its limitations, however, as it conflates inferred mental states with both their causal antecedents and their observable effects. As Hancock, Desmond, and Matthews (2017) note, fatigue is more accurately conceptualised as a mental state with neuropsychological bases that mediate between the factors that give rise to it and its consequent effects on task performance,

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health, and subjective feeling states. This distinction carries significant theoretical implications, since the relationship between the causes and effects of fatigue is not direct but is mediated by underlying brain mechanisms — a consideration that explains why this relationship does not conform to the linear pattern assumed by earlier fatigue models (Kahneman, 1973). It is for this reason that a considerable body of scholarly work has proposed that neuropsychological mechanisms function adaptively, serving to compensate for the adverse effects of fatigue on performance and wellbeing (e.g., Hockey, 1997).

Whilst this definition identifies the possible causes and effects of fatigue, it does not specify the brain mechanisms that mediate between them. An accurate definition of fatigue must therefore take into account, as illustrated in Figure 5, that fatigue is a state inferred from the relationship between its causes and effects. Accordingly, it is necessary to postulate the brain mechanisms that mediate between these causes and effects in order to adequately explain and predict the relationships between them.

To investigate the possible brain mechanisms underlying the effects of fatigue, it is necessary to first review the research conducted to date on the relationship between the causes and effects of fatigue, as this body of work may shed light on the neurological mechanisms that mediate between them.

As an illustrative example, consider the impact of "Time on Task" (TOT) on fatigue. Hockey's (2013) review of research on this effect identifies several key findings:

- **Performance decrement is not universally observed:** A decline in performance is not consistently associated with time spent on a task. Even in tasks of considerable duration and high demand, performance decrements may not be observed.
- **Performance decrement is more prevalent in repetitive tasks:** Reductions in performance are more frequently documented in tasks that are highly repetitive, fast-paced, and continuous in nature.
- **Performance decrement increases with higher workload:** Performance decrements tend to be more pronounced when the task imposes a higher level of mental workload and requires a greater degree of effort.
- **Performance recovery through rest or task change:** Recovery of performance is achievable through rest and/or a change of task, particularly when the substituted task does not place additional demands on mental resources.
- **Resistance following prolonged effort:** Following extended periods of intense effort, individuals exhibit a marked resistance to sustaining that level of exertion.
- **Rapid performance decrement in certain conditions:** Under certain conditions, performance decrements may manifest rapidly, in some cases after as little as five minutes of task engagement.
- **Lapses in fast and continuous tasks:** Fast-paced and continuous tasks are frequently characterised by an increase in lapses — interruptions in performance that are typically preceded by a slowing of responses and an increase in errors, and followed by a subsequent return to faster and more accurate performance.

The complexity and variability of these findings render them fundamentally incompatible with any theoretical account premised on a simple linear relationship between time spent on a task and the progressive onset of fatigue. A more sophisticated explanatory framework is required, one that postulates neurological mechanisms capable of accounting for such phenomena as the elimination of the Time on Task (TOT) effect on fatigue when the individual transitions to a more cognitively engaging activity, the documented interaction between mental workload and TOT, and the well-established tendency for performance decrements to manifest with greater frequency and severity in tasks characterised by repetitiveness and monotony.

An equally important theoretical requirement is the postulation of brain mechanisms capable of accounting for the dissociation that may occur between the various possible effects of fatigue. The EU definition identifies two such effects — alertness and performance — which do not consistently co-occur in individuals experiencing fatigue. Alertness is typically operationalised through the subjective feeling of fatigue, whilst performance is assessed by reference to the quality and accuracy of task execution. Beyond these two dimensions, fatigue may also manifest in a range of psychophysiological parameters, including cortical electrical activity as measured by EEG, pupil dilation, and blink rate (Dawson et al., 2011). A significant limitation of the EU definition, however, is its failure to specify whether all possible effects of fatigue will necessarily present concurrently. It does not address, for example, whether an individual who reports subjective fatigue will inevitably experience a decline in task performance, or whether adequate performance levels may be maintained notwithstanding the presence of fatigue.

Experimental findings suggest a distinct dissociation among the observable effects of fatigue. Specifically, the subjective experience of exhaustion often fails to align with objective performance declines or variations in psychophysiological indicators of arousal. A salient example of this decoupling occurs during prolonged driving, where operators may sustain high levels of performance despite perceiving themselves as fatigued. In these instances, psychophysiological metrics often reveal a sustained state of activation, highlighting the complexity of fatigue as a multi-dimensional construct (Muñoz-de-Escalona et al., 2020; Pütz et al., 2024).

Consequently, it is imperative to delineate a neural mechanism capable of accounting for the intricate relationship between the etiologies and manifestations of fatigue. A primary candidate for such adaptive regulation is the **Compensatory Control Model (Hockey, 1997)**. According to this framework, a specialized monitoring system evaluates the cognitive effort required to execute a selected **Optimal Method (OM)** by comparing task demands against available physiological resources. Should the required effort exceed current capacity, compensatory mechanisms are recruited to mobilize additional resources, thereby maintaining performance at an asymptotic level. However, this mobilization is constrained by the brain's finite energetic capacity. Once these metabolic or cognitive thresholds are reached, the monitoring system performs a strategic cost-benefit analysis to determine whether to sustain resource allocation or transition to a less demanding operational mode.

The model posits that prolonged task engagement leads to a progressive depletion of available cognitive resources, a state fundamentally characterized as fatigue. Crucially, however, the onset of this state is mediated by adaptive mechanisms capable of mobilizing supplemental resources to sustain performance at optimal levels. Consequently, the transition into a fatigued state is largely contingent upon the efficacy of these compensatory systems; by augmenting the resource pool, they effectively attenuate the rate of depletion and delay the functional impact of exhaustion.

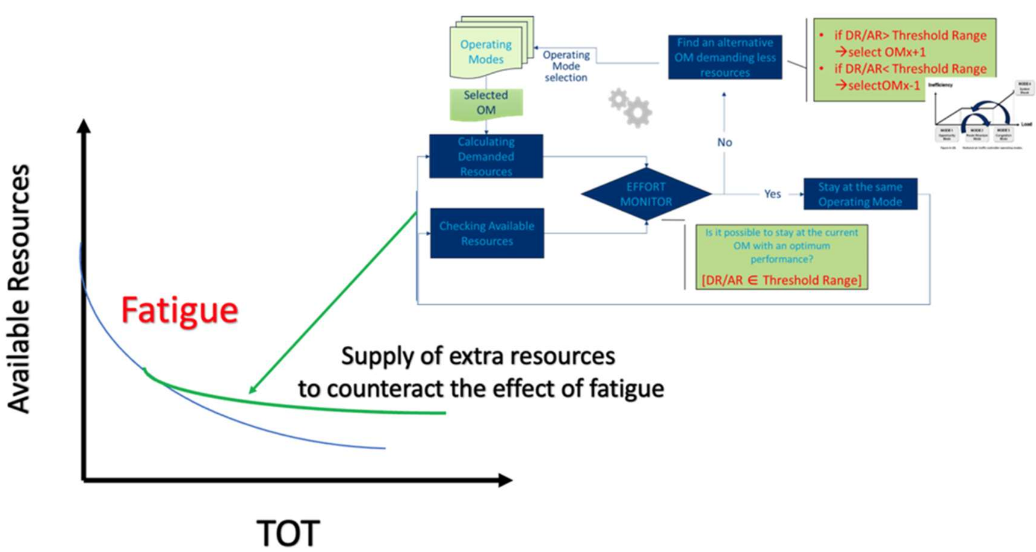

Figure 5. Mental fatigue as a decrement on available resources.

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Within the framework of Hockey's Compensatory Control Model (1997), subjective fatigue serves as a critical signaling mechanism, an 'alarm' generated by the Effort Monitor to indicate the impending depletion of resource reserves. Notably, task proficiency may be maintained despite the emergence of this signal, as performance decrements only manifest once a specific 'critical threshold' of available resources is breached. This model posits a temporal dissociation: the subjective sensation of tiredness (Hockey, 2013) invariably precedes the attainment of this physiological threshold. Throughout this process, fluctuations in psychophysiological parameters serve as objective indices, reflecting the dynamic state of the resource pool and the compensatory effort being exerted before a shift in the operating mode becomes necessary.

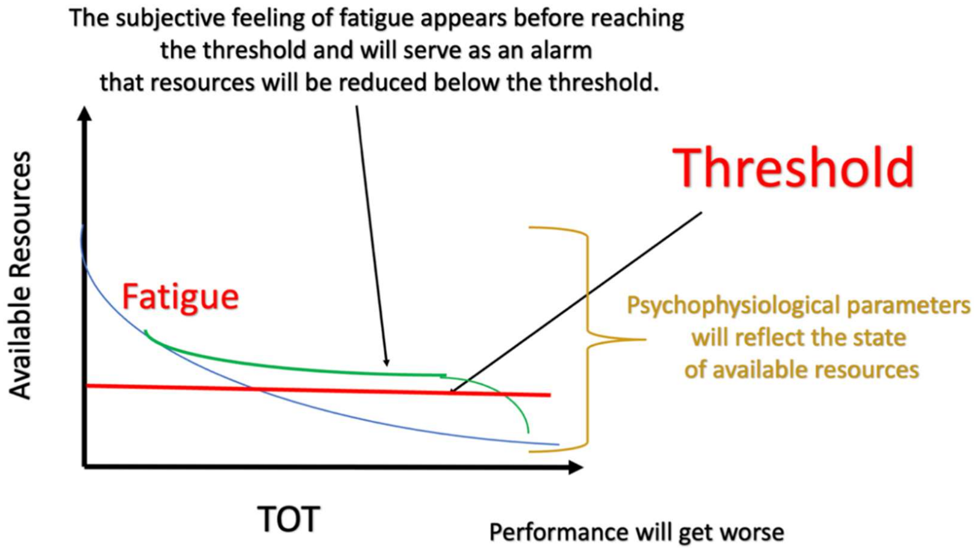

Figure 6. The effects on performance, psychophysiological parameters, and subjective feeling of fatigue.

The neural architectures responsible for effort evaluation and resource regulation are conceptualized as a dual-system framework comprising facilitatory and inhibitory mechanisms. These systems dynamically manage the depletion of resource reserves inherent in sustained task engagement (Ishii, Tanaka, and Watanabe, 2014). Specifically, the **facilitatory mechanism** is recruited when situational demands necessitate the mobilization of supplemental cognitive resources to maintain performance. Conversely, the **inhibitory mechanism** serves to attenuate resource allocation when task demands diminish or when the metabolic cost of the effort outweighs the perceived benefit (see Figure 7). This homeostatic balance ensures that resource expenditure is optimized relative to the evolving requirements of the operational environment.

The Facilitatory Mechanism

Electroencephalographic (EEG) evidence indicates that the induction of mental fatigue is accompanied by an up-regulation of the sympathetic nervous system. This physiological response reflects a compensatory increase in motivation or cognitive effort designed to mitigate the deleterious effects of fatigue on task proficiency. For instance, heightened motivational states have been shown to facilitate performance stability during cognitively demanding tasks, effectively counteracting the functional decline typically associated with prolonged mental exertion (Boksem et al., 2006).

The Inhibitory Mechanism

Conversely, the inhibitory mechanism fulfills a vital homeostatic function by generating signaling cues that prevent fatigue from compromising biological equilibrium, thereby facilitating

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systemic recovery (Boksem & Tops, 2008). Neuroanatomical studies have implicated the insular cortex (IC) and the posterior cingulate cortex (PCC) as key structures within this inhibitory circuit. These regions are thought to integrate interoceptive signals and evaluate the metabolic costs of continued exertion, ultimately prompting a reduction in resource allocation to protect the organism's physiological integrity.

The **insular cortex (IC)** has been positively correlated with the subjective sensation of fatigue in immunological models (Harrison et al., 2009) and is increasingly recognized for its role in the cognitive evaluation of mental effort (Otto et al., 2013). Under low-demand conditions, the inhibitory mechanism functions as a homeostatic alarm system, signaling the requirement for rest and resource replenishment. This mechanism underpins the subjective experience of fatigue that emerges over time, even in the absence of observable performance decrements. However, as task demands intensify, available resources progressively dwindle and converge toward the critical threshold established by the effort monitor. At this juncture, the inhibitory mechanism signals that resources are nearing total exhaustion. Once this threshold is reached, the facilitatory mechanism can no longer mobilize supplemental reserves, necessitating a strategic transition in the operating mode to prevent further physiological strain.

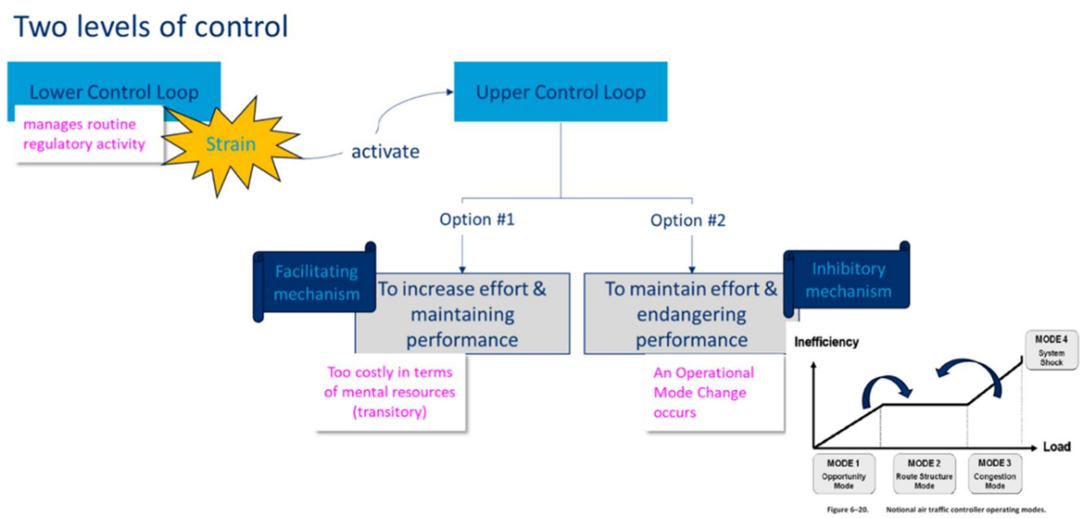

Figure 7. The facilitatory and inhibitory mechanisms that monitor and act on available resources.

The CODA model focuses exclusively on task-contingent variables, intentionally excluding non-task-related factors such as sleep deprivation, prolonged wakefulness, circadian phase, or individual chronotypes. Within this framework, empirical evidence confirms that Time on Task (TOT) results in a progressive reduction of available cognitive resources, a phenomenon observed across all levels of task demand. Paradoxically, however, the relative impact of TOT is attenuated under high-demand conditions compared to low-demand settings (van der Linden et al., 2003; Nakagawa et al., 2013). This interaction is characterized by distinct resource depletion functions: while high cognitive complexity necessitates a greater absolute expenditure of resources, the rate of depletion and the resulting functional sensitivity to TOT vary significantly according to the task's demands (see Figure 8).

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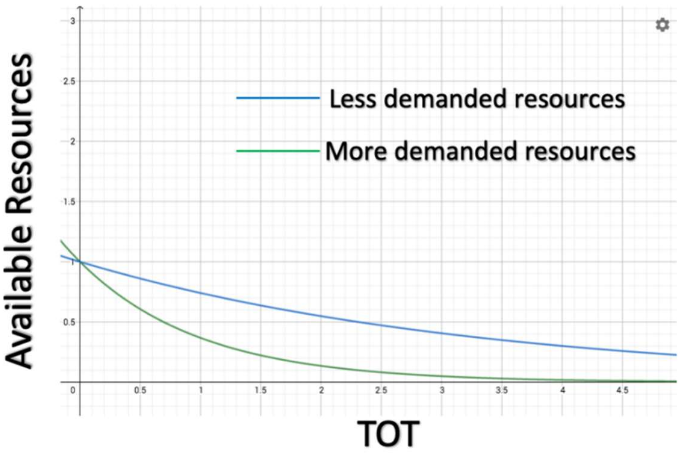

Figure 8. The decrease of available resources as a function of demanded resources.

Furthermore, the mitigation of fatigue is facilitated through periods of rest or via inter-task transitions, particularly when subsequent tasks do not impose supplemental cognitive loads. In operational environments such as air traffic control, the strategic integration of low-demand intervals within a shift may serve as a functional recovery phase. These periods of reduced mental taxation allow for the partial replenishment of available resource reserves, thereby attenuating the cumulative effects of fatigue and sustaining the operator's long-term performance stability.

6.3. Stress

In contrast to fatigue, which originates from the progressive depletion of cognitive reserves, stress constitutes an active evolutionary mechanism designed to mobilize and supply resources to the organism. Within this framework, stress is defined as the physiological substrate responsible for the generalized response to environmental demands or threats, categorized as stressors (Selye, 1956). This response functions as an integral component of the organism's homeostatic architecture, operating to maintain an adaptive equilibrium and ensure protection when confronted with adverse environmental conditions.

While stress is fundamentally situated within the homeostatic system, this paper adopts the more nuanced concept of '**allostasis**' to define the specific regulatory processes under investigation. Allostasis refers to the flexible and dynamic physiological responses recruited to meet environmental demands (McEwen, 1998), whereas homeostasis traditionally describes the maintenance of the organism's overall internal stability. For instance, physiological parameters such as blood pressure, heart rate, and glycemic levels exhibit predictable fluctuations—decreasing during sleep and elevating during strenuous physical exertion relative to baseline. However, the transient, adaptive modifications triggered by environmental stressors are characteristic of an allostatic system, which emphasizes stability through change rather than the maintenance of a fixed set point.

The allostatic mechanism is of particular relevance to the current framework, which seeks to model air traffic control tasks within constrained temporal windows—environments frequently characterized by the emergence of acute operational hazards. As established, the stress response is elicited by a stressor, which may be defined as any stimulus or event perceived as a threat. Crucially, this perception is governed by an individual's subjective cognitive appraisal rather than the inherent properties of the stimulus itself. Consequently, the potency of a stressor is highly idiosyncratic; a stimulus that triggers a significant physiological response in one individual may fail to elicit a comparable effect in another, depending on their perceived coping resources and previous experience.

From the perspective of an air traffic controller, a stressor emerges from a perceived discrepancy between the requisite operational state and the controller's appraisal of the current and projected

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traffic environment. The requisite state is defined as an environment characterized by conflict-free traffic flow, safety, and efficiency, wherein the controller possesses sufficient temporal margin to maintain a robust mental model (the primary output of Situation Awareness) and execute proactive decision-making. The perceived state encompasses a discrete temporal window during which the operator assesses the traffic evolution from the present moment to a future horizon. If an impending conflict is identified within this window (either via direct perception or through anticipatory mental simulation) it is categorized as a stress-inducing event, triggering compensatory allostatic mechanisms.

In formulating a robust stress model, it is essential to account for the multi-factorial variables that modulate the allostatic response. The emergence of a stressor precipitates an immediate escalation in task-related resource demands, eliciting a systemic stress response designed to mobilize supplemental resources. The magnitude of this mobilization is intrinsically linked to the temporal proximity of the stressor's onset, as well as its perceived severity and duration; specifically, more acute or protracted stressors necessitate a proportionally greater recruitment of cognitive and physiological reserves. By designating T0 as the point of initial exposure to the stressor, various mathematical functions can be employed to model the recruitment kinetics—differentiating between a rapid, high-intensity surge and a more gradual, sustained distribution of resources over time (see Figure 9).

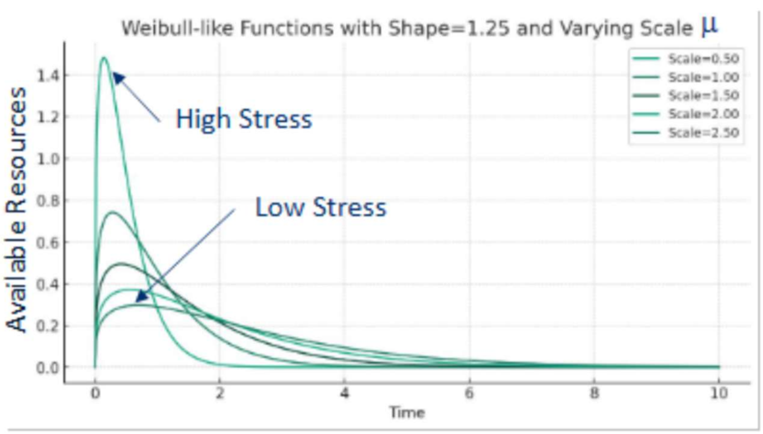

Figure 9. Stressors severity and impact on available resources.

Regardless of the initial recruitment kinetics, this resource mobilization eventually reaches an asymptotic limit beyond which further increases are physiologically untenable. This subsequent decline corresponds to the 'exhaustion phase' originally delineated in the General Adaptation Syndrome (Selye, 1956). During this phase, the stress mechanism fails to sustain the mobilization of supplemental resources required to mitigate environmental demands, leading to a precipitous reduction in available cognitive reserves. It is at this juncture that the operator experiences a profound increase in perceived mental effort and the onset of acute fatigue. This phenomenon is driven by the fact that the cessation of the compensatory stress response results in a more abrupt and rapid depletion of resources than would occur under baseline conditions. Consequently, Figure 9 illustrates the synergistic impact of stress and fatigue: while high stressor severity elicits a more robust initial increase in available resources (AR), the post-stressor period is characterized by a significantly steeper decline due to the cumulative effects of fatigue.

Furthermore, mental workload and fatigue may be conceptualized as emergent properties of the energetic management mechanisms that underpin the allostatic stress response. This perspective underscores a reciprocal causality: while the mobilization of resources in response to stress frequently precipitates elevated mental workload and subsequent fatigue, the inverse is equally significant.

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Excessive cognitive demands and the resulting state of exhaustion are, in themselves, perceived as stressors. This creates a self-reinforcing cycle wherein the demands of task execution and the biological costs of resource depletion continuously interact to modulate the operator's functional state.

Although a stressor for one individual may not have the same effect on another, in this CODA model two stressors are identified:

1. Acute Demand Escalation (Sudden Surges)

A rapid, non-linear increase in task demand while an operator is managing baseline traffic levels constitutes a primary acute stressor. This sudden spike necessitates the accelerated processing of information and high-stakes decision-making under severe temporal constraints. Such conditions elicit an immediate up-regulation in arousal, thereby augmenting available resource reserves. The abrupt nature of this escalation often generates a perception of imminent operational risk, as the controller may perceive traditional safety margins and standard protocols to be compromised. Consequently, stress levels intensify as the operator strives to mitigate potential conflicts and preserve the integrity of safe operations.

2. Sustained High-Workload Saturation (Prolonged Demand)

The second stressor involves the experience of sustained high-intensity workload, requiring protracted periods of maximal cognitive effort and vigilance. Unlike acute spikes, this chronic demand induces a state of persistent mental fatigue, as the controller must continuously integrate complex data streams while maintaining operational safety. The stress arising from the awareness of diminished performance capacity can paradoxically trigger further activation; the operator enters a compensatory state, mobilizing additional reserves to uphold rigorous safety standards despite deteriorating functional conditions and the onset of exhaustion.

6.4. Sustained Attention

The burgeoning interest in sustained attention and vigilance research within the field of Human Factors has been significantly catalyzed by recent advancements in automation technology. Such automated environments are exemplified by air traffic control systems, where the vigilance decrement remains a critical determinant not only of systemic reliability but also of broader public safety (Warm et al., 2015). As automation increasingly shifts the operator's role from active control to passive monitoring, understanding the cognitive underpinnings of vigilance becomes essential for mitigating human error and ensuring operational resilience.

In a qualitative study involving expert interviews within the Ergonomics and Human Factors domains, Kyriakidis et al. (2015) reported a near-unanimous consensus: the primary impediment to automation achieving its projected efficacy is the inherent difficulty human operators face when performing monitoring-centric tasks. This 'monitoring paradox' necessitates a rigorous examination of the cognitive architecture underlying supervisory control, a role that has become the linchpin of human-machine collaboration. To optimize the design of automated systems, it is essential to define the parameters of the monitoring task and systematically identify the psychological and physiological constraints that compromise its execution.

To synthesize current research on process monitoring, it is imperative to disambiguate its terminology from related constructs such as vigilance and sustained attention—terms that, while often conflated, possess distinct theoretical boundaries. **Monitoring** is defined as the multidimensional process of attending to information from disparate sources to identify, sustain, modify, or interpret a target activity. Within the context of process control, monitoring encompasses a tripartite functional architecture:

- **(a) Detection:** The sensory reception and filtering of environmental stimuli.
- **(b) Cognitive Integration:** High-level decision processes involving the synthesis, interpretation, and conceptualization of sensory input.

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- **(c) Execution:** The implementation of behavioral responses aligned with previous cognitive appraisals.

Consequently, monitoring is not a passive state but an active, iterative cycle of observation and diagnostic reasoning, where the operator continuously evaluates system states to inform future interventions.

Of these functions, the initial stage—detection and sensory reception—has historically dominated the empirical landscape. Within Human Factors, this component is systematically investigated through the vigilance task, which requires operators to maintain an unfaltering attentional focus on a target stimulus to detect infrequent signals over extended durations. It is functionally evident that the vigilance task constitutes a critical sub-component of the broader monitoring process; specifically, it addresses the signal-detection requirements necessary to inform subsequent decision-making.

In cognitive psychology, proficiency in these tasks is attributed to the underlying construct of sustained attention. Consequently, sustained attention is defined as the endogenous mechanism responsible for maintaining a state of high sensitivity and alert readiness over prolonged temporal windows (Warm, Parasuraman, & Matthews, 2008). In this framework, sustained attention serves as the physiological and cognitive substrate that facilitates vigilance, which in turn enables the overarching monitoring task.

Extensive empirical research spanning several decades has consistently identified a significant attenuation in signal detection—typically ranging between 10% and 15%—within the initial 30 minutes of task engagement. Following this primary decline, performance continues to deteriorate, albeit at a decelerated rate. This phenomenon is formally recognized in the literature as the **vigilance decrement**, which serves as a primary metric for quantifying the limitations of sustained attention. While traditional models suggest that this decrement typically manifests after approximately 15 minutes of continuous exertion (Teichner, 1974, as cited in Warm et al., 2008), subsequent findings demonstrate that its onset is highly sensitive to task complexity. Specifically, under conditions of elevated cognitive demand, the functional decline can accelerate significantly, manifesting as early as the first 5 minutes of task performance (Helton, Dember, Warm, & Matthews, 2007; Warm et al., 2008).

Early empirical inquiries into the vigilance decrement have traditionally navigated between two divergent theoretical frameworks. The first perspective—the Under-arousal Hypothesis—posits that performance deterioration stems from the suppression of cortical activity during monotonous and repetitive tasks, leading to a state of diminished alertness. Conversely, the second approach assumes that while available resources are inherently finite, they remain constant over time. This assumption of resource stability allows researchers to shift the focus toward the dynamic distribution of these limited reserves within multi-task environments, such as air traffic control.

Within this framework, performance fluctuations are not attributed to a net loss of capacity, but rather to the interference of extraneous variables (e.g., sleep deprivation, circadian rhythm shifts). Fortenbaugh, DeGutis, and Esterman (2017) modeled this phenomenon, illustrating that although the total resource pool may remain stable, the proportion dedicated to the primary task is subject to significant variance. As shown in Figure 10, an operator may initially allocate maximal resources to the primary monitoring task; however, as the task progresses, a significant portion of these reserves may be diverted toward internal distractions or 'mind-wandering' (self-generated thought). Consequently, the operator experiences a heightened perception of cognitive effort as they struggle to maintain task-relevant focus against the encroachment of non-task-related mental processes.

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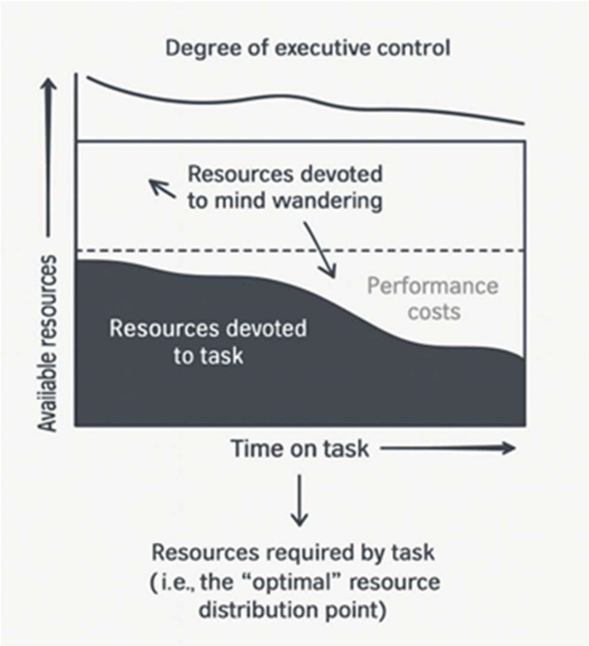

Figure 10. Resource control model of Sustained Attention after Fortenbaugh, DeGutis, and Esterman (2017).

Extensive empirical evidence indicates that the vigilance decrement is modulated by a constellation of situational factors, among which **workload** is paramount. Within the vigilance paradigm, workload dictates the extent of information-processing capacity recruited at any given moment. In the air traffic control environment, this construct manifests through a bimodal distribution: ranging from high-demand scenarios—requiring the simultaneous management of multiple tasks and frequent tactical interventions—to low-demand conditions characterized by monotonous, repetitive monitoring with minimal operational variety. This 'double effect' of workload is well-supported by research, suggesting that both cognitive saturation and cognitive under-stimulation can critically impair the stability of sustained attention.

In scenarios characterized by monotony and repetition, Robertson et al. (1997) posit that attentional effort diminishes as task execution becomes increasingly routinized and 'thoughtless.' This transition toward automaticity suggests that as the controller's primary task requirements fall below a critical threshold, the available cognitive resources are systematically reallocated to task-irrelevant thoughts. Under these low-demand conditions, the phenomenon of **mind-wandering** emerges as a dominant cognitive state.

Paradoxically, according to the **Resource Control Model**, the operator must then exert supplemental mental effort to inhibit these internal distractions and sustain performance on the primary monotonous task. As temporal pressure accumulates and fatigue manifests, the internal regulatory system loses its capacity to maintain this inhibitory control. Consequently, the onset of fatigue acts as a catalyst, significantly exacerbating the **vigilance decrement** by reducing the total pool of resources available for both task execution and the suppression of task-irrelevant thoughts.

In high-demand scenarios, operators are required to carry out several interventions concurrently. Under these conditions, an opportunity-cost framework becomes applicable, given that finite resources must be allocated across all tasks being performed. Driven by their commitment to effective task execution, operators will endeavor to establish task priorities by systematically assessing the cost implications of each activity.

A further consideration is that high task demand, or the subjective perception of heightened difficulty, may precipitate stress. In accordance with the stress model, the introduction of a stressor increases the availability of cognitive resources, thus permitting adequate task execution over a finite period. Within this framework, vigilance decrements bear a negative relationship to stress levels,

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meaning that, upon stress onset, the characteristic decline in vigilance is temporarily attenuated. This effect persists until the additional resources are fully depleted, whereupon resource levels begin to decline once more as fatigue emerges.

At the cortical level, sustained attention is subserved by a distributed network encompassing the frontoparietal network (Petersen & Posner, 2012), the cingulo-opercular system — alternatively known as the salience network (Menon & Uddin, 2010) — and the default mode network (Danckert & Merrifield, 2016). This network, which shows a predominant right-hemisphere lateralization, is considered essential for sustaining arousal and selectively attending to task-relevant stimuli, as well as for the reorientation of attentional resources following attentional errors or momentary lapses (Fortenbaugh, DeGutis, & Esterman, 2017).

At the subcortical level, sustained attention is supported by the locus coeruleus-norepinephrine (LC-NE) system (Aston-Jones & Cohen, 2005), which plays a central role in modulating prefrontal cortex representations in response to attentional control demands (Cohen et al., 2004). In particular, the LC-NE system is implicated in the regulation of attentional state, with fluctuations in its functioning associated with variations and lapses in attention (Mittner et al., 2016).

Within the proposed theoretical framework, decrements in vigilance have been linked to the emergence of mental fatigue. A growing body of evidence suggests that sustained attention tasks give rise to mental fatigue through the activation of a central inhibitory system and/or the deactivation of a central facilitatory system within the central nervous system. These opposing systems are implicated in the neural mechanisms that underlie mental fatigue and are understood to modulate activity across task-relevant brain regions, ultimately regulating cognitive performance (Tanaka, Ishii, & Watanabe, 2014).

Furthermore, sustained attention tasks have been associated with increases in beta-frequency band power in the right inferior and middle frontal gyri (Brodmann areas 44 and 9, respectively). Notably, increased beta-frequency band power in the right middle frontal gyrus was negatively associated with self-reported mental stress and positively associated with boredom and drowsiness (Tanaka, Ishii, & Watanabe, 2014).

7. The Predictive Model

Previous sections have served as the foundations for a software model. This section presents the different elements and main functional requirements that define the predictive mental model software. To predict mental states, a predictive model must define how demanded and available resources are calculated first.

7.1. Demanded Resources Calculation

Demanded Resources are calculated building on a computerised model developed by CRIDA and UGR that calculates the ATCo Cognitive Complexity based on ATCo mental abstractions due to the task load expected (Lopez, Parla, Ballestín, Cañas, Ferreira, Comendador, Lucchi, 2018; Suárez, López, Puntero, and Rodriguez, 2014). The existing formula for the cognitive complexity calculation is composed by different factors based on the hypothesis that any situation that does not assist the controller in making abstractions generates complexity for the controller. The factors selected with the help of operational experts from ENAIRE to construct the Cognitive Complexity algorithm are: Standard Flow Interaction, Potential Crossing Severity, Flights in Evolution, and Flights Outside Standard Flows.

The model outputs equivalent flight counts — that is, flight counts weighted by complexity factors. The metric employed is the occupancy count, defined as the number of aircraft present within a specific airspace sector over a given time period. Figure 11 illustrates the counts for a particular airspace sector during a one-hour window (15:00–16:00). The blue line represents the number of flights in the sector (i.e., the occupancy counts) sampled at 5-minute intervals and updated every minute. The height of each bar represents the complexity count over the corresponding interval. When the total bar height falls below the occupancy value, certain flights are not contributing to any

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complexity factors; conversely, when it exceeds the occupancy count, some flights are contributing to complexity through involvement in multiple factors, such as a flight within a standard flow interacting with another flow, a flight outside any standard flow, or a flight in evolution. The different bar colours denote the distinct complexity factors contributing to the total complexity within each interval.

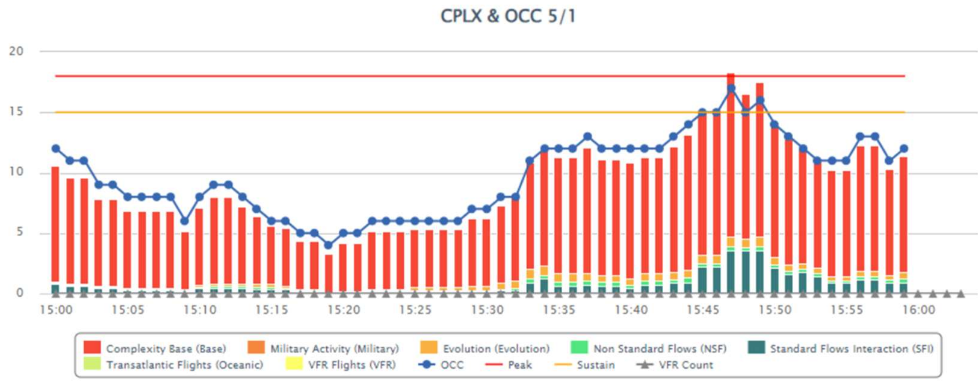

Figure 11. Output of the Cognitive Complexity Tool.

7.2. Operational Mode Prediction

In order to calculate the demanded resources, it is first necessary to establish the Operational Mode (OM) in which the Air Traffic Controller (ATCo) is operating at the commencement of their shift (T0). The assignment of an Operating Mode at T0 is determined on the basis of occupancy counts, that is, the number of aircraft simultaneously present within the sector. The applicable OM is selected from four predefined Operating Modes: OM1 (Opportunistic Mode), OM2 (Route Structure Mode), OM3 (Congestion Mode), and OM4 (System Shock).

After X minutes, the ATCo selects an appropriate Operational Mode (OM) based on task demand and resource availability, in accordance with Compensatory Control Theory. The model then assesses the resource requirements of the chosen OM and compares them against currently available resources. Should a resource deficit be identified, the system endeavours to augment the resource pool. Subsequently, the system monitors the operator's effort to sustain the selected OM within the constraints of available resources while maintaining optimal performance. If performance deteriorates or resources become depleted, a new OM is selected and the cycle repeats. Conversely, if available resources are found to be excessive, the system transitions to an alternative OM in order to optimise energy consumption.

Cognitive complexity was subsequently recalculated as a function of the Operational Mode. Currently, the cognitive complexity tool is calibrated for ENAIRE sectors based on the OM under which those sectors are expected to operate under normal conditions — namely, Operating Mode 2 (Route Structure Mode). The four factors incorporated into the model for OM2 are: (1) Standard Flow Interaction, (2) Potential Crossing Severity, (3) Flights in Evolution, and (4) Flights Outside Standard Flows.

The tool has also been adapted to calculate the cognitive complexity for all Operating Modes: OM1 (Opportunistic Mode), OM3 (Congestion Mode) and OM4 (System shock).

- As for OM1, there are few flights, mental abstractions are not necessary hence factors (1) and (4) are not considered.
- For OM3, the factors will be the same as for OM2 but the base complexity associated to a flight will be smaller than for OM2 to comply with the hypothesis of compensatory Control Theory.

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- For OM4, there is no time to build a mental picture due to the high time pressure and the number of flights. The formula would be the same as for OM1. The selection of this mode by the ATCo is not chosen to reduce complexity and better manage the available resources.

It is assumed that, for equivalent occupancy values, Cognitive Complexity follows the ordering OM1 > OM2 > OM3. This assumption is grounded in the thesis of Histon and Hansman, who posit that when ATCos perceive that complexity is approaching their internal tolerance limits, they are expected to transition toward simpler, less demanding modes of operation. Accordingly, the formula should reflect that, for equivalent occupancy values, Cognitive Complexity under OM1 is greater than under OM2, as the ATCo transitions from OM1 to OM2 with the expectation of managing traffic with reduced effort and, consequently, lower complexity.

7.3. Available Resources Calculation

The computational model for available resources (AR) provides its output in equivalent flight counts meaning flight counts shaped by the identified factors, as in the DR model. The factors that have been considered to shape AR are fatigue and stress.

When T=0, the AR are at its maximum, as CODA only focuses on impacts within the air traffic control tasks. This value is maintained during the initial 10 minutes. Afterwards the Available Resources: decreases or increase in accordance with predicted impact of fatigue, existence or not of recovery factors, and the impact of any stressor identified. The exact impact of modelling of these factors is detailed in the mental states prediction section.

7.4. Mental States Predictions

Mental Workload Prediction

Mental workload is defined as the ratio between resources demanded and resources available. More formally, mental workload is the result of dividing resources demanded by resources available. The result shall be a qualitative value represented by a H, M or L. When a task demands more demanded resources than ATCo possesses (available resources), it results in mental overload, that is a H value. Conversely, when the demand for resources is less than what is available, it leads to mental underload, that is a L value. At any given moment of time, the formula is:

Fatigue Prediction

Fatigue is a depletion of available resources and, in contrary, high stress implies an increment of available resources. As the model only considers the impact of factors within the task, the initial value of AR is set to the Maximum Available Resource which is considered to be 1.3 times the peak capacity threshold of the sector. This value is constant in the initial 10 minutes. The evolution depends on whether the presence or not of stress, and recovery conditions.

The fatigue model aims to estimate the evolution of an ATCo's fatigue level over the course of a task. Drawing on the frameworks proposed by Hockey (2013) and DeLuca (2005), and following a review of the existing literature on fatigue, two primary factors have been identified as affecting task-induced fatigue: Time on Task (ToT) and task complexity (i.e., demanded resources).

It is important to acknowledge that several additional factors are known to exert a significant influence on fatigue beyond the domain of task execution — including, but not limited to, sleep duration, chronotype, and time of day. However, these factors fall outside the scope of the CODA model, which is explicitly limited to the consideration of variables directly related to task execution.

Both task complexity and Time on Task contribute to the accumulation of fatigue. As task complexity increases, reflected in greater demanded resources, the resulting fatigue is correspondingly greater, leading to a more pronounced decrease in available resources.

Stress also has an impact on fatigue. Following a substantial increase in available resources mobilised to cope with a stressor, and the considerable mental effort this entails, the ATCo begins to

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experience fatigue and available resources start to decline rapidly — at a rate contingent on the effort expended and, by extension, the severity of the stressor.

Conversely, fatigue recovery (understood as the replenishment of available resources) is achieved through rest and/or task switching, particularly when the new task does not impose additional mental resource demands. In the context of air traffic control, periods within a shift characterised by low task demand may facilitate fatigue recovery.

In summary, the factors affecting the fatigue model are:

1. Task complexity (modelled as DR) increases fatigue, which reduces AR
2. Time on Task increases fatigue, which reduces AR
3. Stressors increase fatigue after stressor disappearance, which reduces AR
4. Easy tasks after high demanding tasks allows to reduce fatigue, which increases AR

After the initial ten minutes fatigue reduces AR following the formula below, where k is a constant:

$$AR_t = AR_{t-1} * k * e^{-DR*t}$$

Identification of Recovery Periods

The predictive model needs to identify those recovery periods where fatigue is recovered. There must be a change of task demand to consider recovery periods where ATCO is able to recover from fatigue. Fatigue recovery means a recovery of available resources with low demanding tasks (low complexity) after high complexity (DR=H or VH). A low demanding period is when DR = L that is when OM = OM1.

After the initial ten minutes the computation model for AR due to the recovery periods effect follows the formula below, where m is a constant, and T_R is the time since the initiation of the recovery time:

$$AR_t = AR_{t-1} + mT_R$$

As previously mentioned, this formula indicates that the Available Resources increase during the time of recovery. The model will provide qualitative values for Fatigue depending on the existing AR: H, M, L. The lower AR values are, the higher the fatigue is.

Stress Prediction

The model calculates the effect of stressors on the available resources. Within air traffic control, two stressors are identified (2 and 3 are subcases of the same stressor):

- Stressor 1, S1, (rapid increase of demanded resources), meaning that in windows width of X minutes, DR comes from L to H, or from M to VH);
- Stressor 2, S2, (being experiencing high demanded resources) and this occurs when ATCo selects OM3;
- Stressor 3, S3, (being experiencing high demanded resources) and this occurs when ATCo selects OM4.

The severity of the stressors (higher severity means higher increase of AR) is S1<S2<S3.

After the initial ten minutes, if there is stress, the effect of stress on AR follows the formula below where x_i is related to the severity of the stressor, being 0.2 for S1, 0.3 for S2 and 0.4 for S3:

$$AR_t = AR_{t-1} * (1 + x_i)$$

The model will provide qualitative values for Stress (H, M, L) depending on the existing stressors and their impact in AR. If there are stressors and AR are high, the stress will be high.

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Vigilance Decrement Prediction

Fatigue may adversely affect performance in vigilance tasks such as air traffic control. In monotonous and repetitive tasks, attentional effort tends to decrease as task execution becomes increasingly automatic and requires less conscious deliberation. This automaticity promotes the reallocation of mental resources toward other processes, thereby giving rise to mind wandering. Consequently, the operator must exert deliberate mental effort to sustain performance. As fatigue accumulates over time, a progressive decline in vigilance ensues.

In contrast, high-demand tasks require simultaneous interventions, and resources are distributed among these tasks. The ATCo prioritizes tasks based on their cost. Additionally, high demand or perceived difficulty can cause stress, which initially increases resource availability, allowing tasks to be performed adequately for a time. However, once these extra resources are exhausted, fatigue sets in, causing a decline in vigilance. As a consequence, the Vigilance Decrement Calculation will be dependent on Fatigue existence. Vigilance decrement is not affected if fatigue is low, and vigilance decrement appears if fatigue is medium or high. The models provides two outputs: High vigilance if no vigilance decrement is detected, or Low vigilance y vigilance decrement is detected.

8. Data Collection for Estimation of Mental Model Parameters

The predictive mental model was initially calibrated using information from real operations within Spanish airspace. These parameters were refined and completed in a simulation of air-traffic control by using a set of scenarios that provoke the target mental reactions in the controllers. The following approach has been followed to calibrate the parameters of the model:

- STEP 1 – Based on expert judgement, different scenarios were design to provoke different levels (H, M, L) for mental workload, fatigue, stress and vigilance. These scenarios were designed by manipulating occupancy levels to induce changes in the demands on cognitive resources and, therefore, cognitive complexity. The scenarios were located in the same Spanish airspace preciously used.
- STEP 2 – Once these scenarios were designed and modelled in the simulation platform, the model parameters were set to induce the desired mental states. Active air traffic controllers performed the control task in both scenarios.
- STEP 3 – The data collected during the control sessions were used to calibrate the model parameters. The logic behind this calibration consisted of testing the hypotheses derived from the model. The analysis focused on identifying common patterns across participants for each mental state: Several dependent variables were measured to infer those mental states. Those dependent variables were:
    - Workload was assessed using ISA values, blinking data and EEG-workload signals.
    - Stress was assessed using EEG-stress signals and DSSQ questionnaire scores.
    - Fatigue was assessed using EEG-fatigue signals and SOFI-SM questionnaire scores.
    - Vigilance was assessed using blinking data and EEG-vigilance indicators.

8.1. Method

Scenarios

Several traffic samples from real-world traffic data from 2023 were used to produce the target mental states in the controller. The traffic samples were labelled in terms of traffic demand and traffic complexity, along with the mental states that are expected to occur within each scenario. These hypotheses (expected mental states per scenario) were identified based on the factors that usually provoke mental workload, mental fatigue, stress and vigilance that has been previously described in the Cognitive Prediction Model section.

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The expected mental states have been labelled with L (Low), M (Medium) and H (High) values. OM refers to the Operating Mode that the ATCo is using to cope with the traffic. Four operational modes were defined: Opportunity mode (Mode 1), Route Structure mode (Mode 2), Congestion mode (Mode 3), and System Shock mode (Mode 4). Two scenarios were modelled and tested to provoke the different Mental States. One with an increase from low to medium occupancy/complexity, another one with steady high complexity.

The computerised model developed by CRIDA and UGR that calculates the ATCo Cognitive Complexity based on ATCo mental abstractions due to the task load expected was run with the occupancy planned in the scenarios (Lopez, Parla, Ballestín, Cañas, Ferreira, Comendador, Lucchi, 2018; Suárez, López, Puntero, and Rodriguez, 2014). Was run to test that in these two scenarios occupancy appropriately affects the resources demanded and, therefore, the cognitive complexity supported by the controllers, as is shown in Figure 12, the values of cognitive complexity follow the values of occupancy directly. The first scenario, SC1, presents an occupancy (orange line) and complexity (blue line) that increases from low to medium values. The second scenario, SC2, presents a steady high occupancy and complexity. (see Figure 12). Therefore, we can see the scenarios were effectively designed to manipulate demanded recourses.

SC1 – OCC/complexity and hypotheses	SC2 – OCC/complexity and hypotheses

Figure 12. Two scenarios in which the controllers worked during the simulation.

In these two scenarios, with the initial parameters of the model we could predict the following hypotheses:

- In SC1 the model predicts an increase in Mental Workload. The values would go from L to H. However, in SC2, the increase of workload will go from M to H.
- Fatigue should appear in both scenarios, but it should be greater in SC2 than in SC1. This is because the controller endured a higher demand on resources due to a high complexity state that persisted throughout the scenario.
- Stress should increase in both scenarios. In SC1, the continuous increase in complexity should lead to an increase in stress. However, in SC2, maintaining a high level of complexity is also a factor that affects stress, causing it to rise.
- Regarding the level of vigilance, we should expect this level to decrease in SC2 because the controller must withstand a high level of resource demand. This decrease should not be observed in SC1.

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Participants

Air Traffic Controllers (ATCOs) provided by International Federation of Air Traffic Controllers' Associations, IFATCA, participated in the simulation.

Procedure

A human in the loop exercise was used to validate the mental model prediction through a series of scenarios within a small-scale Real-Time Simulation (RTS) during five days. The simulation platform used was ESCAPE light developed by Eurocontrol (Bouchal, Had and Bouchudon, 2022). In each scenario, physiological and subjective measurements were collected. Physiological measures were electroencephalography (EEG), and eye-blinking, the subjective measurements were Instantaneous self-assessment (ISA; Jordan and Brennen; 1992),

Before and after the execution of the controllers in the scenarios, they were administered the Swedish Occupational Fatigue Inventory (SOFI; Ahsberg, Gamberale and Kjellberg, 1997), and Dundee Stress State Questionnaire (DSSQ; Matthews et al., 1999). The purpose of these questionnaires was to verify that manipulating occupancy effectively affected fatigue and stress levels at the end of the simulation. The other dependent measures provided data on mental states during the simulation, and we were interested in knowing if there was an overall effect at the end of the simulations.

8.2. Results

This section presents the results for three controllers and two scenarios together with the analysis performed on the data. Except for the dependent variable ISA, the results are presented in graphs where the dependent variables are plotted against time. The results of moving means are shown to allow for the inspection of any trend changes in these variables that might correspond to changes in the controllers' mental states. In the case of the ISA variable, a correlation analysis was performed between this variable and the Occupancy variable.

The results for each dependent variable are presented below. When explaining the results for a dependent variable, its values will be evaluated in relation to the mental states reflected in them. First, the results of the dependent variables measured during the control exercises in the scenarios are presented. Then, the results of the fatigue and stress questionnaires completed by the controllers before and after the control exercises in the scenarios are presented.

Dependent Variables Measured During the Performance in the Scenarios

ISA

The subjective measure known as ISA (Instantaneous Self-Assessment) was used to evaluate the changes in workload. ISA is a simple, subjective workload measurement tool used primarily in real-time or near-real-time operational settings (Jordan, and Brennen, 1992). It captures the operator's perceived workload at specific moments during a task. ATCOs are asked to rate their current mental workload every 3 minutes, and they select a rating on a five-point ordinal scale, ranging from 1 (very low) to 5 (very high workload). In this experiment, a pop-up window appeared on the screen to collect the ATCO's feedback. During the ISA analysis next values were assigned to the different answers:

- If ISA < 2, then workload is assigned a L value;
- If 2 <=ISA < 4, then workload is assigned M value;
- If ISA <=5, then workload is assigned H value.

As ISAs values have small granularity (from 1 to 5), autocorrelation analysis was not appropriate.

Occupancy and ISA values over the 3-minute intervals were subjected to correlation analysis. In Scenario 1, the data showed a very high positive correlation between occupancy and ISA, $r = .95$, $p < .01$. However, in Scenario 2, this negative correlation, although not reaching a sufficiently significant

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level, r = -.21, p = .10. As can be seen in Figure 13, in Scenario 1, mental workload increased significantly as occupancy increased, which we can interpret as the increased demand for resources leading to an increase in mental workload. However, in Scenario 2, a slight decrease in occupancy is observed, but mental workload continues to increase somewhat, perhaps due to the decrease in available resources resulting from sustained high resource demand over a long period.

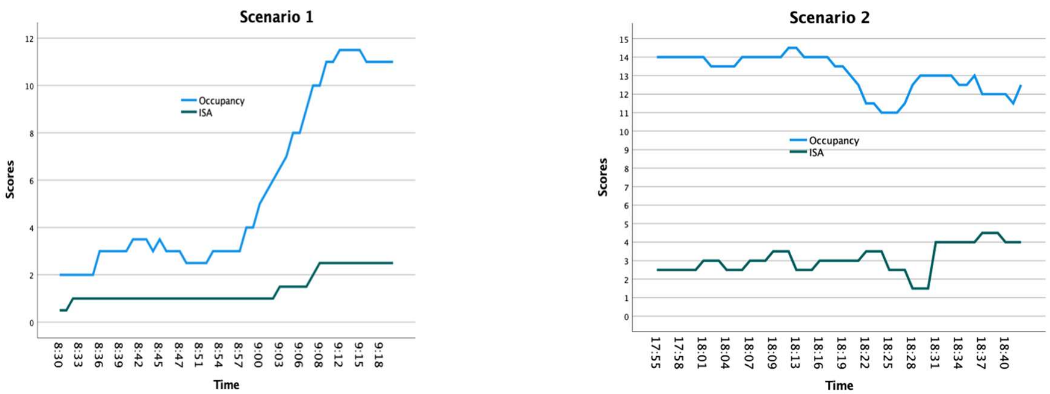

Figure 13. Changes in ISA as a consequence of the changes in Occupancy n Scenario 1 and Scenario 2.

Blinking

The recording of Eye-tracking or ocular tracking is methodology that enables the observation of changes in eye movement patterns, including blink frequency, saccadic movements, and pupil dilation. These parameters are linked to cognitive load, as high-load conditions often result in reduced blinking and more erratic eye movements. Among these ocular parameters, blinking frequency and duration are two of the most robust measures of mental states, as pupil size requires light ambient control and saccades require task-specific interpretation.

Blinking data per ATCO and scenario have been taken as temporal series analysed with rolling means to identify breaking points that could correspond to the hypothezed tendencies in mental estates. It should be noted that in SC1 for ATCO1 the blinking from 8:48 to 9:14 was not recorded and hence the values are discarded.

As presented in Figure 14. Around 8:45, ATCO 2 and ATCO3 have a decrement of blinking frequency as expected according to the Hypothesis (the more workload, the less blinking frequency). Occupancy changes patterns affect the Blinking Frequency for 2 out of 3 ATCOs as initially defined by the hypothesis (the more workload, the less blinking frequency). As can be seen in the figure, around 8:45 there is a change in the trend in the number of blinks. These begin to decrease, indicating an increase in mental workload that corresponds to an increase in occupancy.

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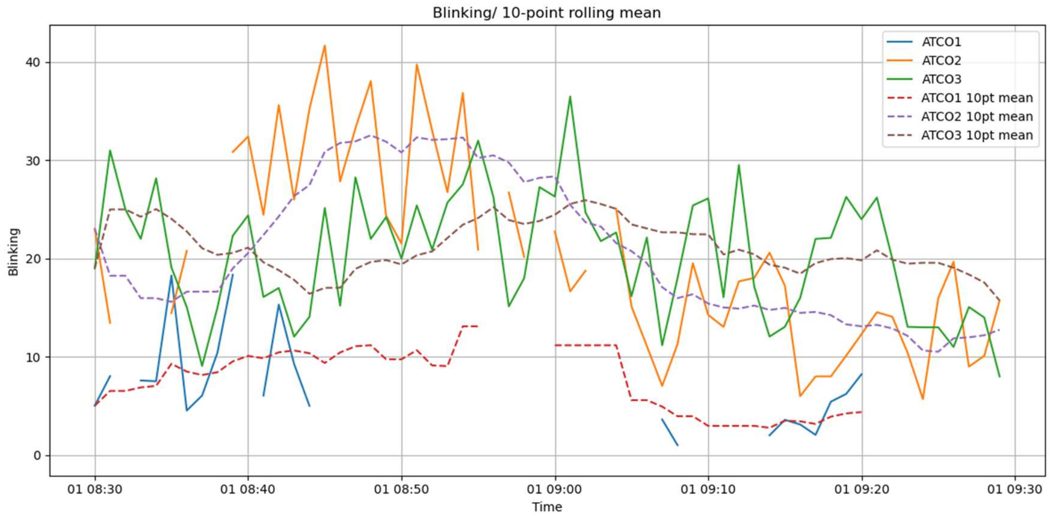

Figure 14. Changes in blinking frequency as a consequence of the changes in occupancy in Scenario 1.

In SC2, we hypothesized that if Mental Workload increases, a decrement of blinking frequency should be expected. But mental fatigue produces the contrary effect on blinking, hence an increment should be observed. In this scenario, none of the ATCOs presented should present a change in blinking frequency. Therefore, as expected, there is no pattern change in blinking frequency for any of the controllers. The explanation is that the opposing effects of WL and Fatigue cancel each other out, resulting in no change in the frequency of blinking (see Figure 15).

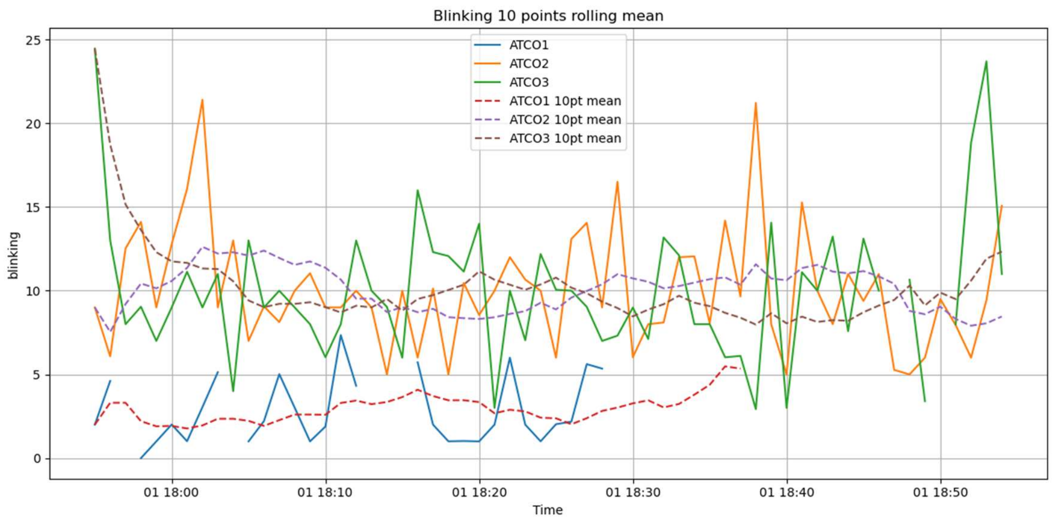

Figure 15. Changes in blinking frequency as a consequence of the changes in occupancy in Scenario 2.

EEG

Electroencephalography (EEG) is a powerful tool for assessing mental states such as workload, fatigue, stress, and vigilance by measuring the brain's electrical activity through sensors placed on the scalp. It captures neural oscillations across different frequency bands, typically delta, theta, alpha, beta, and gamma, which are associated with various cognitive and emotional processes. Among these, alpha EEG activity (8-12 Hz) has been widely studied regarding cognitive workload. Research indicates that alpha band activity tends to decrease as cognitive workload increases, reflecting a state

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of higher mental engagement. For instance, one study evaluating the alpha-to-theta and theta-to-alpha ratios found that these measures, particularly from frontal and parietal electrodes, effectively discriminated between low and high mental workload based on self-reported perceptions (Raufi, and Longo, 2022).

Additionally, high-frequency waves, such as beta (13-30 Hz), are associated with intense cognitive processing (Schmidt et al., 2019) (but their activity may decrease during prolonged tasks, signalling mental fatigue (Jacquet et al, 2021). This dynamic shift, especially in theta band activity, is crucial for understanding mental fatigue during sustained cognitive tasks. Moreover, a meta-analysis further confirmed that alpha power decreases during tasks requiring high mental effort, reinforcing its sensitivity as an index of workload (Chikhi, et al, 2021).

In terms of attention, EEG is widely used to assess sustained attention or vigilance. As time progresses, performance tends to decrease, which is reflected in the EEG as decreases in alpha activity and increases in beta and gamma activity, indicating increased mental effort to maintain attention (Pershin et al, 2023). EEG-based vigilance detection, particularly in contexts such as driving, has been an emerging field, using advanced signal processing models to predict driver fatigue from brain activity [53].

Among the EEG devices available on the market, the controllers' brain activity during the CODA validations was collected by using the Mindtooth Touch system (https://mindtooth-eeg.com/) with 8 water–-based electrodes (5 frontal and 3 parietal channels) and Bluetooth low-energy (BLE) connectivity. This system has been used in several real contexts as described in the works by Di Flumeri et al (2019) and Di Flumeri et all (2022). This system processes the electrical signals recorded by the electrodes and subjects them to algorithms that provide values for Mental Load, fatigue, Stress, and Vigilance.

EEG measurements per ATCO and scenario, have been taken as temporal series with rolling means to identify breaking points that could correspond to the hypothezed tendencies in mental estates. In the analysis of the EEG Workload in SC1, no breakpoints were identified for any ATCO meaning there were no trend changes along the run. EEG Workload did not seem to follow the Occupancy trend changes. Although it slightly increased, this increment was not statistically significant. Occupancy change did not seem to impact the EEG Workload index, as there were no breakpoints for any EEG ATCO workload temporal series. A slight, constant increase along the run was detected, but no pattern change was observed. This constant increase in mental workload was to be expected considering that there was an increase in occupancy from low to medium levels (see Figure 16).

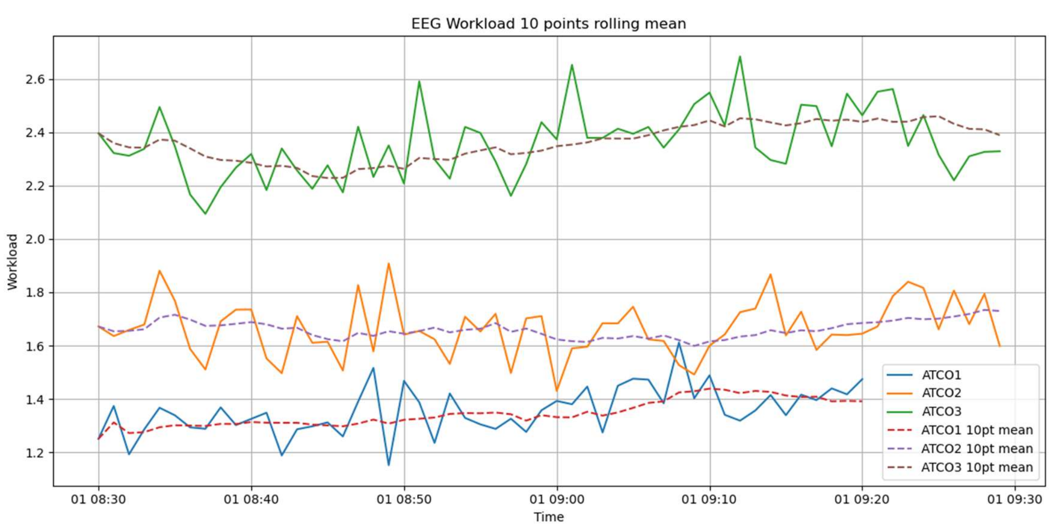

Figure 16. Changes in EEG Workload as a consequence of the changes in occupancy in Scenario 1.

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Regarding EEG Fatigue, no breakpoints were identified for any ATCO in Scenario 1, meaning there were no trend changes along the run. EEG Fatigue did not seem to follow the occupancy trend changes. In general occupancy changes did not seem to impact EEG Fatigue as there were no breakpoints for any EEG ATCO workload temporal series. No pattern change was observed, and even for ATCO 2, fatigue appeared to decay when an increment was expected according to our hypothesis (see Figure 17).

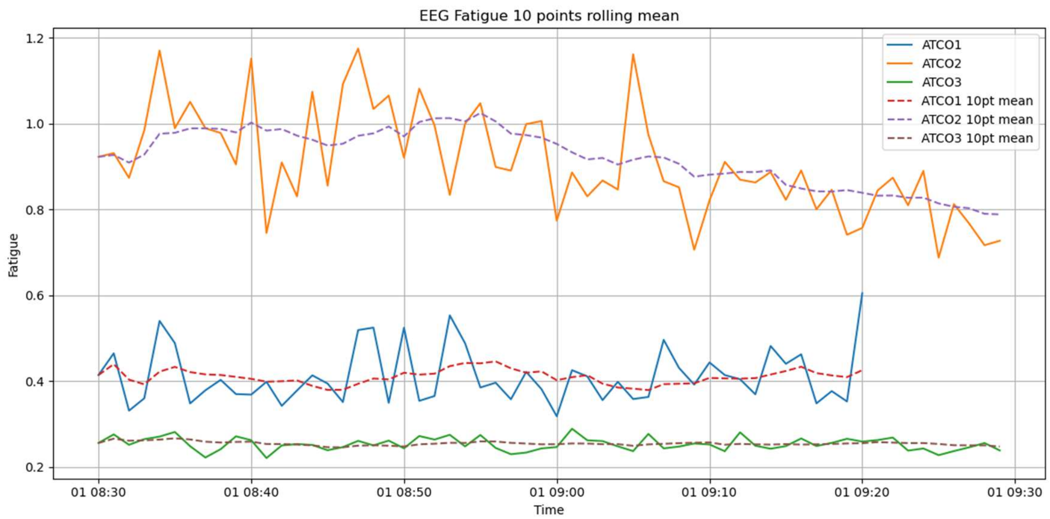

Figure 17. Changes in EEG Fatigue as a consequence of the changes in occupancy in Scenario 1.

Regarding EGG Stress, no breakpoints were identified for ATCO 1 and ATCO 3 in SC1, indicating that there are no trend changes along the run. On the contrary, ATCO 2 stress increases with an increment of occupancy. Occupancy change seems not to impact EEG Stress except for ATCO 2. Therefore, we can say that the EEG results do not confirm our hypothesis regarding controller stress (see Figure 18).

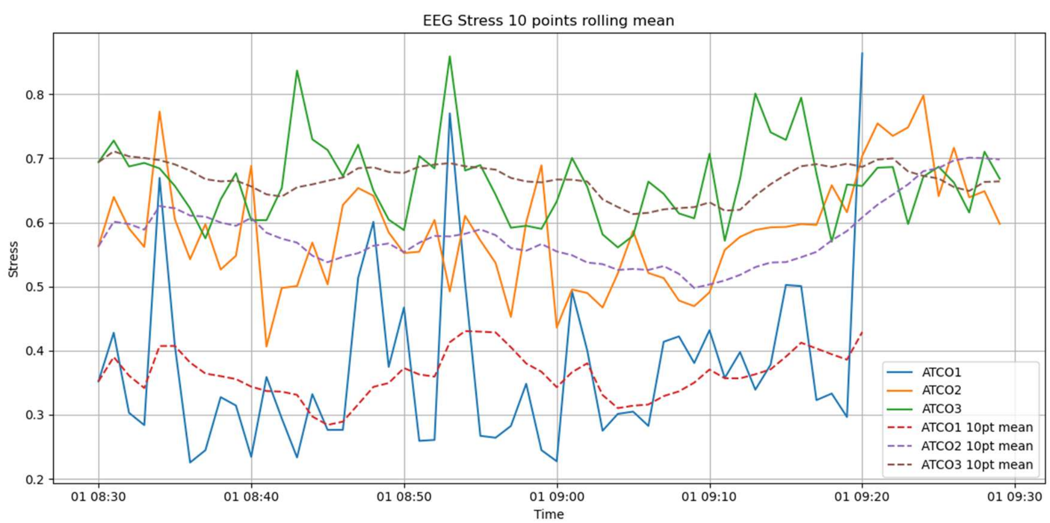

Figure 18. Changes in EEG Stress because of the changes in occupancy in Scenario 1.

Finally, in EGG Vigilance, there was a common breakpoint for ATCO 1 and 3 in SC1 at 09.00, but trends were not consistent. Therefore, we can say that no consistent feedback was obtained in Vigilance in SC1 (see Figure 19).

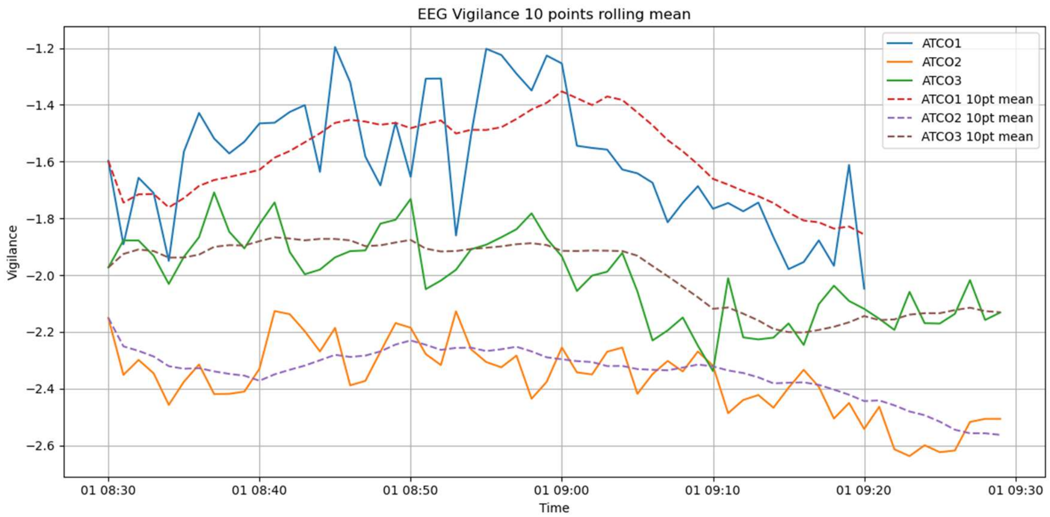

Figure 19. Changes in EEG Vigilance as a consequence of the changes in occupancy in Scenario 1.

Regarding EEG Workload in SC2, breakpoints are not common among ATCOs and not consistent with the Occupancy changes. In the main part of the run, the EEG Workload slightly increases except for ATCO2. Occupancy changes did not seem to impact on EEG WL as there aren't breakpoints for any EEG ATCO workload temporal series. A slight constant increase along the run is detected but there is no pattern change (see Figure 20).

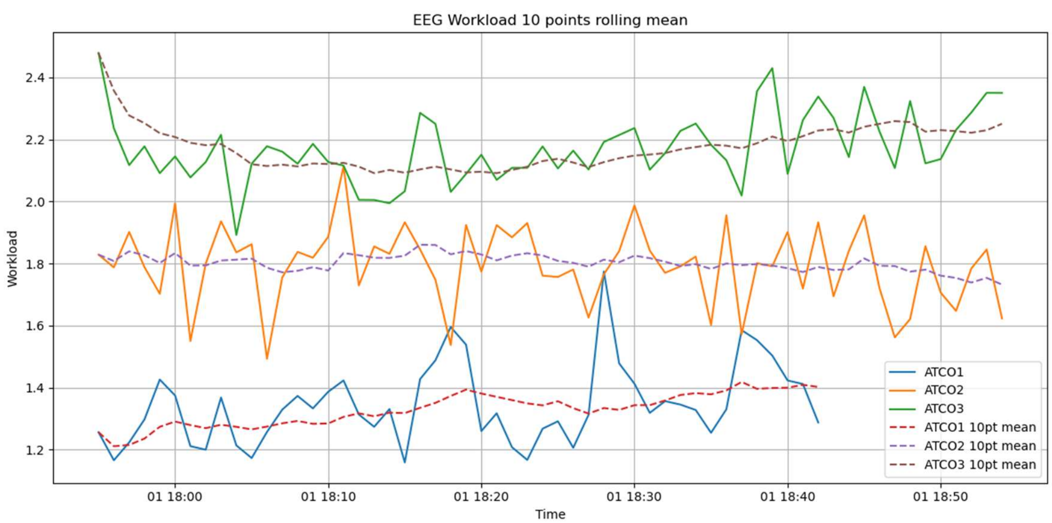

Figure 20. Changes in EEG Workload as a consequence of the changes in occupancy in Scenario 2.

Regarding EGG Fatigue, breakpoints are not common among ATCOs and not consistent with the OCC change. There aren't common patterns. There is no clear pattern on fatigue based on EEG-Fatigue signals (see Figure 21).

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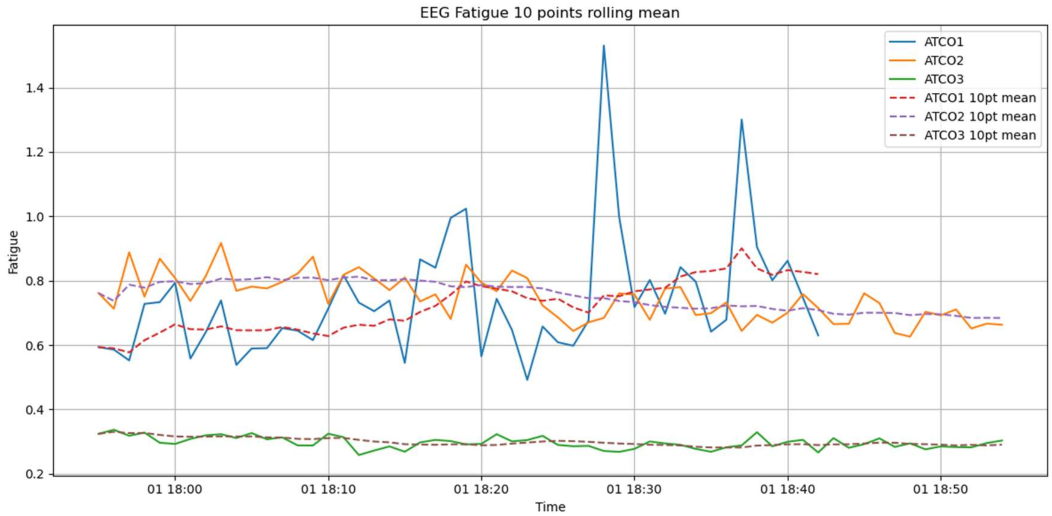

Figure 21. Changes in EEG Fatigue as a consequence of the changes in occupancy in Scenario 2.

Regarding EEG Stress, breakpoints are not common among ATCOs and not consistent with the OCC change except for ATCO 3 who feels an increment of stress with an OCC increase (see Figure 22).

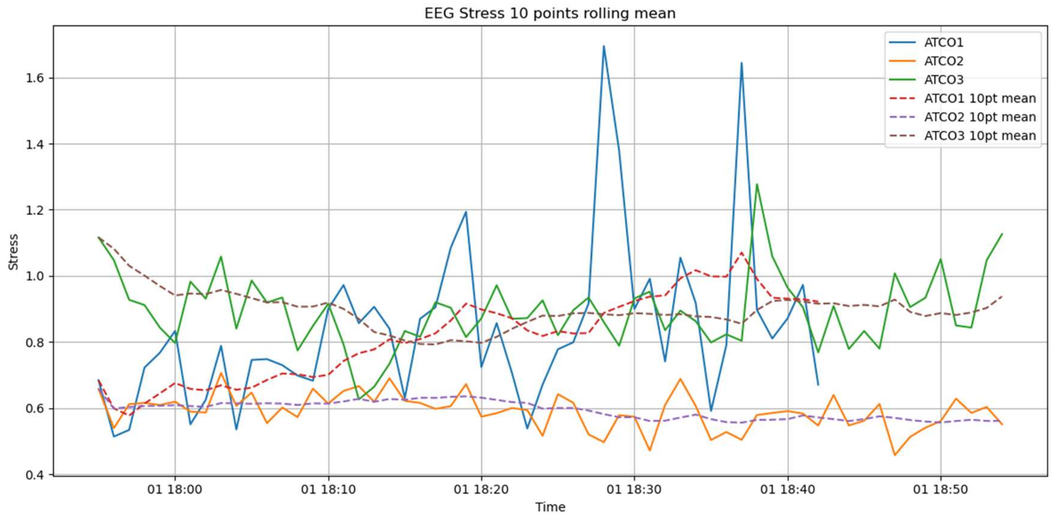

Figure 22. Changes in EEG Stress as a consequence of the changes in occupancy in Scenario 2.

In EEG Vigilance, breakpoints are not common among ATCOs and not consistent with the OCC change. There aren't common patterns. According to the hypothesis, if Fatigue is high there should be an impact on Vigilance. Apparently, this is not appreciated in the EEG data, as there is no clear pattern (see Figure 23).

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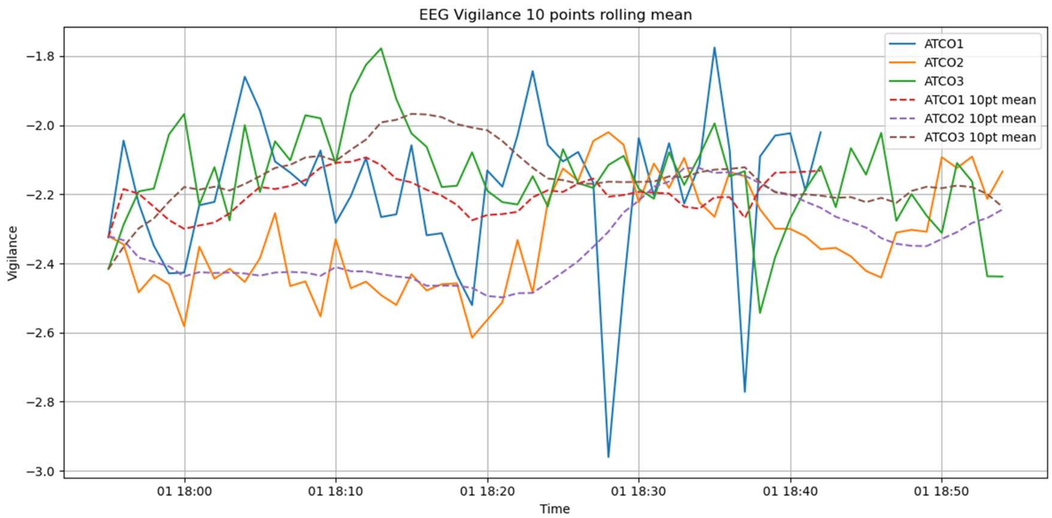

Figure 23. Changes in EEG Vigilance as a consequence of the changes in occupancy in Scenario 2.

Summary of the Results

The following tables summarise the hypothesized results and data trends. Table 1 summarizes the results for Scenario 1. It presents the results for the three ATCOs and the four mental states inferred from the measured dependent variables. The last two rows of the table represent the five proposed hypotheses and a summary of the results. As can be seen, the results indicate that two of the five hypotheses are confirmed. A progressive increase in occupancy leads to a corresponding increase in mental workload and fatigue. However, the increase in occupancy does not result in changes in stress or vigilance levels.

Table 1. Data analysis for Scenario 1 - Low & Medium Load Traffic Demand/ Complexity. "L" means Low, "M" means Medium, and "H" means High.

Scn. 1	OCC	WORKLOAD			FATIGUE	STRESS	VIGILANCE
		ISAs	Blinking Frequency	EEG	EEG	EEG	EEG
ATCO1	L to M	L to M	-----	Slight increase	Constant	Constant	Not a clear pattern
ATCO2	L to M	L to M	Change with OCC. Decrease	Slight increase	Constant	Decrease à Increase	Not a clear pattern
ATCO3	L to M	L to M	Change with OCC. Decrease	Slight increase	Slight decrease	Constant	Not a clear pattern
Hypothesis	L to M		L to M		L to L/M	L to L	No Impact
Overall Outcome	L to M		L to M		L to L/M	L to L	No Impact

Table 2 summarizes the results for Scenario 2. As can be seen, the results for mental workload and fatigue again align with the hypotheses. However, in this scenario, an effect of occupancy on stress and fatigue does not provide a clear pattern. Although, there was a tendency to observe a change in vigilance as predicted.

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Table 2. Data analysis for Scenario 2 - High Load Traffic Demand/ Complexity. "L" means Low, "M" means Medium, and "H" means High.

Scn. 2	OCC	WORKLOAD			FATIGUE	STRESS	VIGILANCE
		ISAs	**Blinking Frequency**	**EEG**	**EEG**	**EEG**	**EEG**
ATCO1	H to H	M to H	Slight decrease	Slight increase	Slight increase	Slight increase	Constant.
ATCO2	H to H	M to H	Constant	Constant	Decrease	Constant	Not a clear pattern.
ATCO3	H to H	M to H	Constant	Slight increase	No clear pattern	Decrease to Increase	Decreasing
Hypothesis.	H to H		H to H		L to H	M to H	Impact when Fatigue is H
Overall Outcome	H to H		H to H		No clear pattern	No clear pattern	Impact when Fatigue is H

Questionnaires

ATCOs completed questionnaires designed to capture variations in stress and fatigue. The SOFI, the Swedish Occupational Fatigue Inventory and the DSSQ-3 – Dundee Stress State Questionnaire (Short Form) before and after every run. The reason for distributing these questionnaires was to verify that the manipulation of resource demand in the scenarios was truly effective. We expected fatigue to be greater in both scenarios, but mainly in scenario 2 where resource demand was constant throughout the run. However, we did not expect a change in stress in either scenario. In scenario 1, occupancy did not reach levels high enough to pose a stress risk. In scenario 2, occupancy was constant, and there were no situations that caused changes that would stress the controllers.

The SOFI, the Swedish Occupational Fatigue Inventory**,** is a self-report questionnaire designed to assess perceived fatigue in occupational settings. It captures multidimensional aspects of fatigue, going beyond physical tiredness to include mental and emotional dimensions, to measure fatigue variation before and after the run. The questionnaire consisted of 20 items belonging to 5 dimensions: lack of energy, physical exertion, physical discomfort, lack of motivation, and sleepiness. ATCOs were asked to rate each item on a Likert scale from 0 to 7. A score of 0 meant they did not experience the feeling indicated by the item at all, while a score of 7 meant they experienced it completely. The scores for the items corresponding to Lack of Motivation, Sleepiness, and Lack of Energy were averaged to provide a total score for those dimensions. We were not interested in physical exertion or physical discomfort, so those items were excluded from the analysis of the results.

As shown in the Figure 24, in scenario 1, the drivers showed increased fatigue in all three dimensions analyzed. The Wilcoxon signed-rank test was significant for all three dimensions ($z = -2.11$, $p < .05$). In scenario 2, the differences between administration before the run and administration after the run were also significant ($z = 2.37$, $p < .05$). The effect of fatigue was greatest in the Energy dimension, although the differences between the three dimensions in the post-run administration were not statistically significant (see Table3).

DSSQ-3 – Dundee Stress State Questionnaire (Short Form**)** is a shortened version of the Dundee Stress State Questionnaire, developed to assess momentary psychological stress states in task or performance settings. The DSSQ-3 is based on the idea that stress is not a single thing, but a combination of affective and motivational states that change with the task. The questionnaire consisted of 30 items belonging to 3 dimensions: Task Engagement, Distress, and Worry. The controllers assigned a score to each item on a Likert scale with values between 1 and 5. The scores were calculated as the mean of the items corresponding to each subscale.

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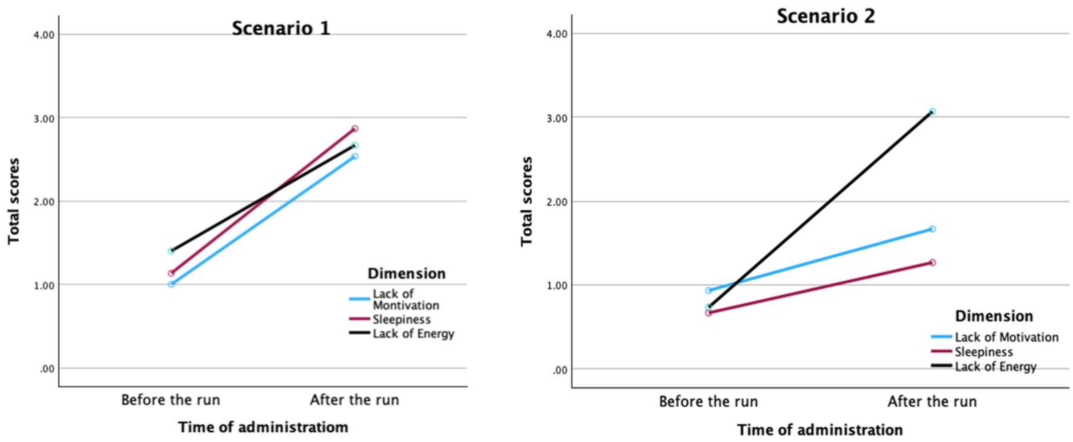

Figure 24. Results of the SOFI Questionnaires before and after the run.

As can be seen in Figure 25, the three dimensions showed different patterns before and after the run. In scenario 1, the three dimensions remain constant, indicating that the controllers remain engaged in the task during the run and they maintained the same levels of distress and worry. The Wilcoxon tests showed no significant differences between conditions ($p = 1$). Feelings of worry were lower than feelings of distress, and these were lower than feelings of involvement even before the control task began. Significant differences were observed between the three conditions, according to the Friedman test ($\chi^2(2) = 6$, $p = .05$, $W = .36$). In scenario 2, the questionnaire scores also showed that feelings of worry were lower than those of distress, and these were lower than feelings of involvement, even before the control task began. The Friedman test ($\chi^2(2) = 4.66$, $p = .09$, $W = .36$) was close to significant. However, unlike what happened in Scenario 1, involvement in the task was lower, and feelings of distress increased after the control task, to such an extent that the differences between the three dimensions ceased to be significant. The Friedman test was not significant ($\chi^2(2) = 2$, $p = .37$).

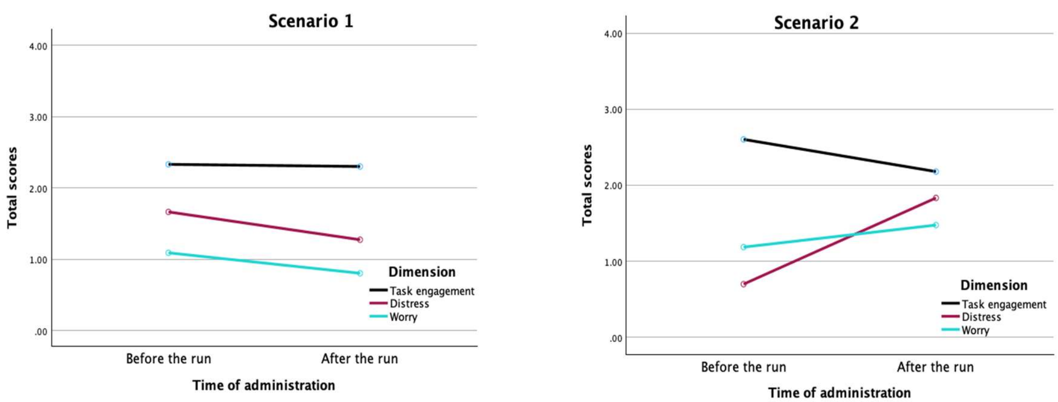

Figure 25. Results of the DSSQ-3 Questionnaires before and after the run.

Therefore, the results of the fatigue and stress questionnaires confirmed that the manipulations that were introduced in the scenarios to provoke these mental states were successful and support the results obtained on these two mental states in the dependent variables measured during the execution of the control task (see Table3).

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Table 3. Questionnaire analysis for Scenario 1 and 2 - L" means Low, "M" means Medium, and "H" means High.

Scn. 2	FATIGUE	STRESS	FATIGUE	STRESS
	SOFI	EEG	SOFI	EEG
Scenario	1	1	2	2
Hypothesis.	L to L/M	L to L	L to H	M to H
Questionnaire Outcome	L to M	L to L	L to M/H	M to M/H

9. Discussion

The model, developed within the CODA project, was designed to reflect mental states changes as a consequence of the changes on the conditions of the task the air-traffic controllers have to performance. In this paper, we present the results of a study designed to define and calibrate the model and the parameters currently set within it. This task was achieved by designing two scenarios in which occupancy conditions change, and we assume that these changes affect cognitive flexibility—that is, the demand on mental resources—that the controllers bear.

The methodology used consisted of measuring several dependent variables from which the controllers' mental states could be inferred. Those dependent variables were EEG signals, eye-tracking data, and subjective assessments. The exercise demonstrated that the combination of eye-tracking and subjective data (ISA, SOFI-SM, DSSQ) provided more consistent and interpretable patterns, while EEG data alone was too variable across individuals to serve as a reliable calibration source for a general mode. These results suggested that a multimodal approach is essential for reliable mental state prediction in operational contexts.

The concept of mental state modelling was partially validated: predictions for workload and fatigue aligned reasonably well with expectations, while stress and vigilance predictions were less accurate and more static. This suggests that the concept is sound but requires further refinement, particularly in its modelling and interpretation of stress and vigilance.

The technical feasibility of the CODA mental state prediction model, as evaluated in the SESAR exercise, was confirmed at an early development stage. The system was successfully integrated into a realistic simulation environment using the ESCAPE Light platform and processed multimodal data (EEG, eye-tracking, and subjective assessments). However, EEG data showed high variability across individuals, limiting its reliability for general model calibration. As a result, the model relied more on eye-tracking and subjective inputs, which proved more consistent. The model performed well in predicting workload and fatigue, but was less accurate in predicting stress and vigilance.

Overall, the results supported the feasibility of development of mental states prediction model. Therefore, The next steps in our research will be to refine the model parameters so that the prediction of mental states is better and, especially, so that the mental states of stress and vigilance can also be predicted, since with the current parameters it does not seem that an optimal prediction can be obtained.

10. Limitations and Future Work

Several limitations of the present work should be acknowledged. First, the current calibration is based on a limited number of simulation scenarios and participants. Although these simulations were designed to elicit a wide range of mental states, further refinement with larger samples and more diverse operational contexts is required. Second, the model focuses exclusively on task-related factors and does not incorporate non-task influences on mental states, such as sleep quality, circadian rhythms, or individual differences in chronotype. While this restriction was intentional, future extensions of the model could integrate these factors to improve predictive accuracy over longer time horizons. Third, mental state predictions are currently expressed qualitatively. Although this

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approach is appropriate for adaptive automation decisions, future work could explore more fine-grained quantitative representations, as well as probabilistic formulations to account for uncertainty. Finally, further research is needed to evaluate how the model performs when embedded in real-time operational systems and how controllers interact with adaptive automation driven by mental state predictions.

11. Conclusions

This paper presented a cognitive–psychological predictive model of air traffic controllers' mental states, developed within the CODA project. The model integrates theories of cognitive processing, mental resource management, and adaptive strategy selection to predict mental workload, fatigue, stress, and vigilance over time.

Initial simulation-based results provide partial empirical support for the model's assumptions and predictive relationships. By enabling short-term prediction of mental states, the model offers a promising foundation for the development of adaptive human–AI systems that support controllers proactively and intelligently.

More broadly, the proposed framework illustrates how explanatory psychological theory and predictive modelling can be combined to address the challenges of human–AI collaboration in complex socio-technical systems.

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