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A Review of Situational Awareness in Air Traffic Control

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ABSTRACT As demand for air transport continues to grow, the complexity of the operating environment of air traffic has intensified. Air Traffic Controllers (ATCOs) are faced with the critical task of making timely decisions in response to rapidly changing air traffic. In this context, maintaining Situation Awareness (SA) becomes critical, directly influencing ATCOs' decision making and preventing potential traffic accidents or incidents. This paper presents a systematic review of the theoretical development of SA measurement techniques for ATCOs. Firstly, the measurement techniques developed to assess individual and team SA are discussed and summarized. Additionally, some recently developed novel measurement methods are introduced. Four specific techniques applied to evaluate ATCOs' SA are highlighted. Second, the article analyzes the comprehensive utilization of neurophysiological measurement techniques, with a particular focus on eye movement and EEG methodologies. These techniques exhibit promising potential in measuring ATCOs' SA and are explored in-depth. Furthermore, four distinct types of sensitivity factors that primarily affect ATCOs' SA are summarized. This paper provides some insight into the current state of SA measurement techniques for ATCOs. It concludes with recommendations for future research, specifically addressing evaluation of ATCOs SA in high-automation environments.

INDEX TERMS Situational Awareness, Air Traffic Control, Human Factors, Air Traffic Controllers, Human-Automation Teaming

I. INTRODUCTION

IN Air Traffic Control (ATC), the primary responsibility of Air Traffic Controllers (ATCOs) is to ensure the safe and orderly flow of aircraft traffic. Airspace is divided into sectors in which one or two ATCOs are responsible for providing air traffic service to flights. Airspace is characterized by various uncertainty factors, including fluctuations in flight volume, diversified flight paths, variations in aircraft performance, and weather conditions. These factors contribute to the dynamic and ever-changing nature of air traffic, which requires ATCOs to adapt and respond effectively to ensure the safety and efficiency of operations. ATCOs must continuously monitor and analyze real-time information to maintain Situational Awareness (SA) and promptly identify and resolve potential conflicts. Incidents and accidents often result from a deficiency in SA, leading to inadequate decision-making and incorrect actions. For example, the crash of the Lion Air

flight JT610 in 2018 exemplified a breakdown in SA within the control group. ATCOs were unaware of the potential technical failure of the flight and continued to direct other flights to take off and land, resulting in a tragic accident. Statistics from the Australian Transport Safety Bureau show that approximately 85% of accidents are related to a lack of SA. Therefore, enhancing the SA of ATCOs plays a key role in ensuring the operational safety and accurate functioning of the ATC system. Effective SA is essential for managing complex dynamic tasks, as it facilitates better performance outcomes. By maintaining a higher level of SA, controllers can effectively allocate their cognitive resources and achieve better performance.

Situational awareness can be interpreted differently in various fields; however, there is a common understanding that it involves perceiving environmental elements within a specific time and space, comprehending the meaning of these ele-

ments, and predicting future states based on this understanding. Acquisition and maintenance of SA generally encompass three levels. The first level involves collecting sufficient and relevant information through multiple sensory channels such as visual, auditory, and tactile senses. This process allows for a comprehensive and accurate picture of the current environment. The second level involves understanding and processing the information collected to construct an analytical model that reflects the current state of the environment. This involves applying "precision thinking" by integrating and comparing existing knowledge, mental experiences, and observed data. The analytical model is continuously updated as new information becomes available. At the third level, an understanding model is established, which utilizes the most accurate and up-to-date information to anticipate future changes in the environment. By operating at these three levels of SA, air traffic controllers, or human operators, can acquire a holistic and dynamic awareness of their operational environment, enabling them to make informed decisions that optimize both efficiency and safety.

There is a rich history of research on Situational Awareness. In 1988, Endsley proposed a three-level concept of SA: the first level involves perceiving environmental elements, the second level focuses on understanding the current situation, and the third level is related to predicting the future state [1]. Endsley also developed a theoretical framework for SA based on a Cartesian approach, emphasizing that SA relies on past events only to the extent that they impact the present or future [2]–[4]. Kraemer et al. argued that SA is a complex structure that involves constant evaluation, filtering, and aggregation of external information [5]. The study of SA has evolved with time and technology. Understanding of SA has expanded from initially focusing on individual SA to encompassing team SA in complex environments involving multiple stakeholders. Team SA has been defined as the process of perceiving and understanding multiple information elements by multiple individuals to achieve task goals [6], or as the shared understanding of the past, present, and future states of task elements among multiple individuals [7]. Endsley et al. discussed the impact of increasing automation on human SA and introduced the Human-Automation System Supervision (HASO) model, providing recommendations for Human-Computer Interaction (HCI) interface design to improve individuals' trust in automation [8]. The National Academy of Sciences explored team SA in Multi-Domain Operations (MDO) and developed detailed design guidelines for SA using automated systems and Artificial Intelligence (AI) [9]. Team SA involves a "feedback-practice" process in complex environments, utilizing the team's shared information mindset model. The shared thinking model is closely tied to real-world events, improving prediction accuracy and decision-making efficiency. Research on SA in teams contributes to more precise predictions, efficient task decisions, and improved operational efficiency. The timeline in Figure 1 illustrates the theoretical development of individual and team SA.

The importance of situational awareness (SA) in air traffic control cannot be overstated, yet there is still a significant gap in our understanding of how to assess and measure SA capabilities effectively. Situational Awareness Global Assessment Technique (SAGAT) is a widely accepted method for assessing SA, but it has limitations when applied in real-world air traffic control settings. This paper seeks to make new contributions to the field of SA assessment to bridge this gap.

A. CHALLENGES IN ASSESSING SA IN AIR TRAFFIC CONTROL

Before exploring the special characteristics of the research in this article, it is necessary to examine and emphasize the current difficulties encountered in the area of SA assessment techniques. Although existing approaches have opened the door for SA assessment, their restrictions are clear. Generally based on subjective self-reporting, these techniques lack the accuracy needed by the industry, and decisions made in a split second can have long-term effects. The research in this paper seeks to address these restrictions by studying the advantages and disadvantages of comparative methods to investigate other successful methods.

B. UNIQUE CONTRIBUTION OF THIS PAPER

This paper seeks to explore the strengths and weaknesses of existing SA assessment methods in air traffic control. Additionally, our aim is to investigate novel assessment techniques, particularly those that incorporate artificial intelligence, eye movement, and electroencephalography (EEG). Using these advanced technologies, we hope to not only enhance the accuracy of SA assessment, but also gain insight into the cognitive processes of SA. This is different from traditional questionnaire-based assessments and has the potential to provide a more precise and actionable understanding of ATCos' SA.

C. ORGANIZATIONAL STRUCTURE

To guide the reader through our exploration, this paper is organized as follows:

1) Review of existing SA assessment methods

In this section (II), we will thoroughly examine the existing SA assessment techniques and assess their advantages and disadvantages when applied to air traffic control. We will discuss ongoing difficulties and investigate the changing requirements of the industry in evaluating SA with AI techniques.

2) Eye movement and electroencephalography (EEG) techniques

In this section (III), we will explore the possibilities of eye movement and EEG techniques in the evaluation of SA. We will discuss the manifestations, potential uses, and the effect of these technologies in providing new knowledge about the cognitive processes of ATCos' SA.

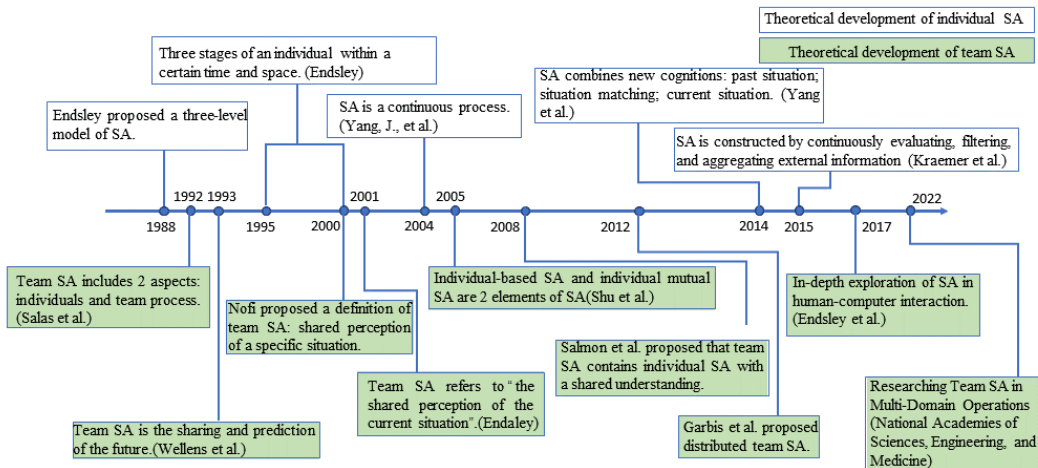


FIGURE 1. The timeline of the theoretical progress of situational awareness for both individuals and teams.

3) Future directions and trends

The last part of this paper (Section IV) will discuss future potential research directions and trends in the field of SA assessment. We will also highlight the potential implications of our results on aviation safety and operational efficiency.

Our main objective is to progress the development of SA evaluation techniques and to gain a deeper understanding of SA for air traffic controllers in the aviation sector. Through a thorough examination of existing methods and the introduction of new techniques, we provide the aviation industry with more reliable SA assessment tools that will eventually improve the safety and effectiveness of air travel.

II. CLASSICAL MEASUREMENT TECHNIQUES FOR SA

We provide an overview of the typical SA measurement techniques from two perspectives: individual and team. We analyze and summarize the main forms of SA measurement methods, as well as their application scenarios, advantages, and limitations.

A. MEASUREMENT TECHNIQUES OF INDIVIDUAL SA

In this section, four different types of SA measurement techniques are discussed: scale assessment methods (e.g. self-report and observer rating), questionnaire query techniques (including online and offline testing), neurophysiological indicators and performance measures. We provide an overview of individual SA measures, including their basic principles, application scenarios, and associated benefits and drawbacks. Additionally, Table 1 offers a comparison of these methods,

highlighting their respective features, advantages, and disadvantages.

1) Scale assessment methods

Scale assessment methods are widely used in SA measurement due to their convenience, ease of administration, and non-intrusive nature (since they are carried out after the task without affecting performance) and high validity. Examples of scale assessment methods include SART (Situational Awareness Rating Technique), QUASA (Qualitative Assessment of SA), SASHA_Q (Situation Awareness for Human Automation Partnerships in European ATM Questionnaire), and CARS (Crew Awareness Rating Scale).

SART has been extensively tested within the context of Rasmussen's skill-, rule-, and knowledge-based behavior model. It has gained wide usage and applicability in various domains, including aviation, cyber security, military operations, submarines, and ground transportation. However, it is important to note that SART is a subjective measurement method, and, as such, is susceptible to reliability issues inherent in all subjective measures. Further development of the SART scale is warranted to improve the reliability of the assessments. This can be achieved through improved item descriptions, adjustments to response intervals, and the application of joint scaling techniques to consolidate multidimensional ratings into a single SA score. Such refinements would contribute to the ongoing advancement and robustness of the SART method.

QUASA is a self-assessment method introduced by

TABLE 1. Summary of individual SA measurement techniques.

Measurement Technology	Author & Time	Features	Advantages	Limitations
SAGAT	Endsley, 1988	Use graphical computer programs to quickly present queries and data collection at specific points in time	Wide range of applications, non-invasive; predictable	Difficult to achieve in reality
SART	Taylor, 1990	Measuring demand, supply, and contextual understanding of attentional resources	Measuring multiple dimensions becomes possible and easy to manage	Highly subjective
SPAM	Durso et al. 1995	Response latency using queries	Response accuracy and reaction time	Invasiveness unknown
SAVANT	Willems & Heiney, 2001	SAVANT provides a 3-second query	The predictive query is effective	There will be a blind spot on the screen
SALSA	Hauss & Eyferth, 2003	Freezing questions combined with expert rating surveys	Effective measurement controller SA	The taxonomy of air traffic is unclear
SASHA_L	Straeter & Woldring, 2003	Online Inquiry	The combination of real-time query and expert rating is objective and effective	Invasiveness is controversial
UASA	McGuinness, 2004	Self-evaluation of the survey presented in the form of right/wrong	Command and control have been effectively proven in exercise missions	Highly subjective
SASHA_Q	Straeter & Woldring, 2003; Jipp & Papenfuss, 2011	Self-assessment questionnaire; the self-assessment level is divided into 6 categories	Effective measurement controller SA	Not involved in forecasting
CARS	McGuinness et al. 2000; Berggren et al. 2011; Stelzer et al. 2013	Eight levels, with scale levels 1-4	Has been successfully used in studies of pilot eye movements, automated trust, etc.	Valid for pilots only
VESARS	Scielzo, 2010; Strater et al. 2013	A software tool that involves individual, team and expert ratings	Can be used to measure SA in virtual and realistic training environments	High cost
Physiological index	Brown, 2002; Nguyen, 2019	Indirect measurement using eye movement index and EEG index	Objective and accurate, easy to operate	High equipment costs; controversial salience
Performance metrics	Watson & Nichols, 1976	Indirect measurement of SA based on reaction speed, the accuracy of task goal completion	Non-invasive and easy to operate	Metric reliability uncertainty

McGuinness [10]. It utilizes surveys presented in the form of right/wrong statements, employing a five-point rating scale (very high, high, moderate, low, very low) along with increasing answer confidence to gauge the accuracy of SA based on the proportion of correct answers. This method has been validated to effectively measure SA in the execution of command and control exercise tasks [10]. However, it still faces challenges related to high variability in individual evaluations and subjectivity in SA measurement.

SASHA_Q is a self-assessment questionnaire that includes questions about SA elements identified by air traffic controllers. It can be used to measure individual or team SA. The questionnaire's items are developed based on actual tasks, and the subjects provide self-assessment scores on a scale of 0 to 6, indicating the frequency of occurrence from "never" to "always". Jipp and Papenfuss [11] applied this questionnaire to validate SA measures for 12 professional tower controllers. However, this method requires more extensive demands and

ordered data for statistical analysis.

CARS is an observer rating technique comprising eight levels ranging from 1 ideal situation to 4 worst situation. Furthermore, CARS has been used to evaluate the relationship between workload, teamwork, SA and performance [12]. However, in an air traffic control experiment conducted by Stelzer et al. [13] on the use of block occupancy displays, the application of CARS did not yield differential effects, indicating certain limitations of CARS in control applications.

The use of scales to assess SA can be beneficial. However, it is important to be aware of the restrictions and potential sources of inconsistency. A difficulty with this type of evaluation is accurately defining the goals. Additionally, discrepancies between subjective experts may lead to doubts about the accuracy of the internal SA assessment.

2) Questionnaire query technique

Questionnaire query techniques are non-invasive methods that allow for the collection of data, enabling real-time assessment of situational awareness. A prominent technique in this category is SAGAT (Situational Awareness Global Assessment Technique), which involves presenting questions to operators immediately after specific events or scenarios. The operator's answers are validated to provide a quantitative measure of SA. Other techniques include SAGAT-Like, SALSA (Situational Awareness for Air Traffic Controllers in an Automated Context), SPAM (Situational Presentation Assessment Method), SAVANT (Situational Validation and Analysis Tool), SASHA_L (SASHA Online), and VESARS (Virtual Environment Situational Awareness Scoring System). These techniques offer a variety of options to objectively assess SA and can be valuable tools in research and practical applications.

SAGAT is an off-line probing technique widely used for scenario assessment in various domains. Initially designed for military cockpit simulations, SAGAT has been extended to applications in aviation, command and control, driving, energy, robotics, and submarine display design. SAGAT assesses different levels of situational awareness, including level 1 data awareness, level 2 meaning understanding, and level 3 near-term prediction. The SAGAT process involves using a graphical computer program to present queries and collect data. During the assessment, the interface is frozen at random time and the participant is asked questions related to the scenario. The participant's answers are compared with correct answers stored in the computer to determine their situational awareness at that specific point in time. The queries can be presented verbally, on paper, or through a computer or tablet interface. SAGAT has been successfully applied in various studies across different domains and experimental settings, demonstrating its noninvasiveness and applicability.

SALSA (Situational Awareness for Air Traffic Controllers in an Automated Context) is an offline probing technique used to measure ATCos' SA in automated scenarios. However, SALSA shares similar limitations as SAGAT, and its process is more complex due to the involvement of experts, resulting in increased time and cost requirements. SPAM (Situational Presentation Assessment Method) is an online probing technique that measures situational awareness based on the precision of responses to queries and response latency. SPAM provides queries related to past, present, and future situations, allowing operators to delay their responses until they are ready to respond, thus assessing situational awareness. Although online techniques offer real-time and objective measurement capabilities, concerns have been raised about the potential intrusiveness of SPAM. Multitasking requirements during operational tasks to answer questions may negatively impact the execution of primary tasks and introduce additional workload interference that could affect actual situational awareness [14]. SAVANT (Situational Validation and Analysis Tool) is an online detection technique that uses data from the air traffic control operating system to assess situational awareness [15].

SAVANT presents a 3-second query asking questions about missing information and evaluates the time taken to answer each question as well as the accuracy. However, similar to other on-line techniques, concerns have been raised regarding its intrusiveness [15].

SASHA_L (Situation Awareness for Human Automation Partnerships in the European ATM Questionnaire, Live) is yet another online detection technique specifically designed for air traffic controllers. It involves an expert who examines the controller's operational display and asks real-time questions related to situational awareness. VESARS (Virtual Environment Situational Awareness Scoring System) is an online probing software tool used to measure the situational awareness of individuals or teams in virtual and realistic training environments. It uses three metrics: real-time situational awareness queries for individual and team assessment, experts' real-time situational awareness behavior ratings for individual and team assessment, and experts' ratings for real-time situational awareness communication [16]. Successful application of VESARS requires clear queries and an expert rating system expert who is highly familiar with the rating system.

Questions about the use of questionnaire query techniques have been raised, particularly in complex and time-sensitive areas such as driving, medicine, and aviation. The debate centers on whether people must gather and combine data from their memory to make appropriate and timely decisions. Additionally, the practicality of executing the "freezing" process in real-world scenarios is a continuing issue.

3) Physiological index

The SA can be quantified on the basis of the data using advanced physiological equipment for eye movement or EEG data recording.

Eye movement technology offers a unique opportunity to access and analyze visual behaviors that people may not be aware of consciously. Capturing individual cognitive processes in the eye movements provides valuable information on and how individuals interact with their environment. This technology establishes an objective and quantifiable link to an individual's situational awareness. Additionally, the use of electroencephalogram devices can be employed to assess an individual's fatigue level, indirectly contributing to the quantification of the link between fatigue and SA. Recent advances in technology have led to the integration of EEG and eye movement data analysis, allowing a more comprehensive understanding of the interaction between eye movements and cognitive processes. This integration involves the use of EEG devices to analyze eye movement data and explore information exchange between the visual system and the brain, specifically the interaction between the optomotor cortex and the premotor area [17]. This approach enables the quantification of the brain-vision interaction and provides a means to characterize situational awareness. Currently, there are several combined technologies that utilize the visual cortex to generate specific signals for eye movement measurement

[18]. These technologies operate on different principles and employ various methods for data collection. Although they differ in form, their underlying principle remains similar, focusing on utilizing the visual cortex to measure and analyze eye movements about situational awareness. Accidents in complex systems centered on humans are often attributed to human error, and a significant factor that contributes to such errors is lack of situational awareness [19]. This lack of SA is often characterized by employees' insufficient understanding of potential hazards and their failure to recognize them. However, advances in science and technology have led to the development of more advanced and convenient neurophysiological measurement devices, which offer valuable assistance in assessing SA. These devices enable the collection of objective and precise information on how individuals perceive their environment [20], [21].

In Section III of this article, a comprehensive overview of eye movement and EEG techniques is presented. These methods make use of neurophysiological measurements to gain insight into how people perceive their surroundings. Using these techniques, researchers can acquire objective and precise data on individual cognitive processes and their interaction with the environment, which can help uncover the mechanisms of SA.

4) Performance metrics

In addition to the aforementioned techniques, performance measures are commonly used as an alternative approach to assess situational awareness. This method involves quantifying SA based on the performance of individuals and the results of the task [22]. The primary objective is to measure SA indirectly by evaluating how well individuals perform in various tasks. To ensure the effectiveness of performance measurement, it is crucial to select performance indicators that are straightforward, easily understandable, and universally applicable. When designing experiments to measure SA, it is advisable to choose stable indicators that enhance the predictability of performance measurement. By doing so, the desired measurement effectiveness can be achieved, allowing for an indirect assessment of situational awareness.

B. MEASUREMENT TECHNIQUES OF TEAM SA

There are six commonly used measurement methods to assess team situational awareness: SAGAT, QUASA, CAST, SASHA_Q, CARS, and VESARS. In addition to providing a comprehensive review of SAGAT, QUASA, and CAST in terms of their principles, application scenarios, advantages, and disadvantages, this subsection focuses on new methods that take advantage of AI techniques. These AI-based methods represent the latest advances in the assessment of team situational awareness. Table 2 presents a comparative analysis of the characteristics, advantages, and limitations of these methods, organized in chronological order of their development. This allows a comprehensive understanding of the evolution and progress in team situational awareness measurement techniques.

1) Traditional measurement techniques for Team SA

The traditional SAGAT measurement method facilitates the simultaneous assessment of all participants within a simulation, allowing the comparison of situational awareness among different team members or sub-teams at the same time [23]–[25]. This approach allows identification of team strategies and bottlenecks. However, a limitation of SAGAT is that it does not support information sharing and exchange between teams, which can impact overall team performance [25].

QUASA, on the other hand, has been validated as an effective method for measuring situational awareness in a 5-person team task [14]. However, this method can be influenced by subjective emotions of team members, resulting in high variability in evaluations among members and subjective measurement of situational awareness.

CAST, developed by Gorman et al. [26], is a theoretical framework for the assessment of team situational awareness. It adopts a process-based approach called the sense of team alignment to the situation. Gorman's research indicates that team flexibility in adapting to dynamic environments is crucial for achieving high team situational awareness scores. CAST allows direct observation of team situational awareness, eliminating the need to infer it from cumulative individual metrics [27]. Unlike questionnaire-based queries that rely on operators' memory retrieval, CAST measures are process-oriented, providing insights into the ongoing process of situational awareness assessment. However, CAST may not be universally applicable and the entire evaluation process can be time-consuming. Additionally, there is no standardized framework for human-set interference in CAST assessments [26].

2) AI-based SA enhancement techniques

In fact, advances in AI technologies have led to their widespread development and application in various fields with the aim of helping humans make decisions and removing them from repetitive tasks. The emergence of autonomous systems and AI has paved the way for Human-AI Teams (HATs) where humans and AI systems collaborate to achieve common goals [28]. Situational awareness has been recognized as a critical factor for effective interaction, understanding, supervision, and prediction within autonomous systems and AI [29]. In addition to the six traditional measurement techniques for team SA discussed earlier, AI-based SA augmentation represents a new and advanced approach for SA measurement and enhancement in human-automated teams. This approach leverages AI technologies to enhance and improve the SA of human operators. By integrating AI algorithms and capabilities, it becomes possible to enhance team SA through intelligent data processing, decision support, and automation. The use of AI-based SA enhancement provides several unique characteristics and advantages,

AI-based SA enhancement techniques can be classified into three main types:

(1) Semantic web and ontology information fusion methods: This approach involves integrating and fusing informa-

TABLE 2. Summary of team SA measurement techniques.

Measurement Technology	Author & Time	Features	Advantages	Limitations
SAGAT	Endsley,1988	Simultaneous assessment of all participants	Identification of team strategies and bottlenecks	Lack of information sharing between teams
QUASAR	McGuinness,2004	Validated for team SA measurement	Easy administration	Subjective variability and measurement subjectivity
CAST	Gorman, 2006	Process-oriented assessment of team SA	Direct observation of team SA	Time-consuming, lack of standardized framework
SASHA_Q	Dehn, 2008; Jipp, 2011	Self-assessment questionnaire for individual/team SA	Measures SA dimensions identified by air traffic controllers	Subjective measurement, data ordering for statistical analysis
CARS	McGuinness et al.2000; Berggren et al.2011; Stelzer et al.2013	Observer rating technique for SA assessment	Effectiveness of automated trust and eye-movement analysis	Limited applicability in certain control applications
VESARS	Scielzo, 2011; Strater et al.2013	Online probing tool for individual/team SA measurement	Real-time queries and behavior ratings	Requires clear queries and expert familiarity with a rating system
AI-based SA enhancement technology	Pai et al.2017; Henaïen et al.2020; Sonia et al.2021; Endsley,2023	Utilizes AI technologies to enhance SA in human-automated teams	Intelligent data processing and decision support	Challenges in AI integration and potential overreliance on automation

tion from various sources using semantic web technologies and ontologies. It leverages the power of inference engines and Knowledge Graphs (KGs) to improve SA. By representing knowledge and relationships in a structured format, this method allows more intelligent information processing and reasoning, leading to better SA. In the study by Pai et al. [30], Semantic Web technology and ontologies were used to address military SA in UAV detection scenarios. SA Ontology (SAO), Military Scenario Ontology (MSO), and Battle Management Ontology (BMO) were utilized for concept modeling and knowledge representation. Multilayer semantic information fusion and rule-based reasoning were employed to provide and augment SA. Henaïen et al. [31] focused on ontology modeling and SA modeling for an IoT-based health monitoring system. They used an inference engine combined with semantic rules and the Fast Decision Tree (FDT) learning algorithm. The proposed system was designed to support enhanced SA and intelligent clinical decision making and prediction. Mehla et al. [32] developed a knowledge base for emergency scenarios using the Web Ontology Language (OWL) and rules. The ontology, consisting of a conceptual knowledge base, instances and processes, aimed to provide background knowledge and information on emergency scenarios for real-time decision making and human recovery from incidents.

(2) Multi-source information data fusion approaches: This type of SA enhancement technique focuses on fusing data and information from multiple sources to generate a comprehensive and coherent situational picture. It involves integrating data from various sensors, systems and sources, such as radar, GPS, cameras and databases. Through advanced data fusion algorithms and techniques, this method aims to extract relevant and meaningful information, reducing redundancy and improving the accuracy and completeness of SA. The use

of KG and inference engines combined with ML modules has been applied in Single European Sky ATM Research (SESAR) as part of the AISA project [29]. This project aims to develop an intelligent SA-aware system for exploring the distributed human-machine SA in ATC operations. Taking advantage of KG and inference engines, along with ML, the system enhances SA in ATC by improving the understanding and decision-making capabilities of controllers. Jiang [33] proposes a representation learning approach based on Graph Neural Networks (GNNs) that addresses the challenge of noisy KGs in AI agents. The approach focuses on learning a joint representation of multiple AI agents to improve prediction integration, data aggregation, representation aggregation and learning predictions. Experimental results demonstrate that collective AI outperforms individual AI, contributing to improved SA through collective intelligence. In Wang et al.'s work [34], a deep learning-based method is presented to fuse multisensor SA data. The approach utilizes an AI data fusion algorithm that combines the classical DS criterion theory with deep learning techniques. Simulation validation shows that the deep learning-based data fusion method is highly efficient and accurate in handling high-conflict environmental information fusion. Future research directions include the combination of adaptive learning and threshold decision techniques of fusion to further improve the effectiveness, speed, and robustness of the system.

(3) Machine Learning (ML) based SA enhancement techniques: ML techniques play a crucial role in enhancing SA by leveraging computational models and algorithms to analyze and learn patterns from data. ML algorithms can be trained on large datasets to recognize and classify patterns associated with specific SA elements or situations. They can also be used for real-time data analysis, anomaly detection, prediction and decision support, helping human operators maintain and



FIGURE 2. Shared SA needs in HAT. (Picture was copied from [37]).

improve their SA.

Interpretable Artificial Intelligence (XAI) is an approach that focuses on improving human understanding and the performance of the human-AI team by providing users with information about the behavior and decision-making processes of AI systems [35]. XAI aims to make AI systems more transparent and explainable, allowing users to trust and collaborate effectively with AI systems. This can be extremely important in human-AI teams, where mutual understanding and cooperation are essential. Sanneman et al. [36] proposed a three-level framework for XAI that aims to develop and evaluate explanations about the behavior of AI systems. They applied techniques such as Grad-CAM and hierarchical associative propagation convolutional neural networks to improve awareness of subliminal persuasive cues. By providing explanations for the behavior of the AI system, users can gain insight into how decisions are made and understand the influence of different factors on AI output. Endsley [37] provided a framework to understand the types of information that must be shared in HATs, including attention to task SA, agent SA, and team SA. The study analyzed an example of a driver using a smart car to illustrate the concept. Effective implementation of cooperative consensus in HATs requires AI systems to understand human goals and plans, as well as to share SA effectively to support optimal teamwork behavior. Figure 2 depicts the concept of shared SA in HATs, highlighting the importance of information sharing and mutual understanding between humans and AI systems.

These studies highlight the integration of AI-based techniques, including semantic web and ontology fusion, rule-based reasoning, and ML algorithms, to measure and improve SA in automated systems, contributing to improved SA in various domains, including air traffic control and multisensor data fusion.

C. MEASUREMENT TECHNIQUES FOR ATCOS' SA

Section II gave a thorough analysis of the methods used to measure situational awareness. Taking into account the distinctive features of air traffic controllers' work, the following section will explore four of the main techniques used to measure their situational awareness in more detail.

1) SAGAT

Endsley et al. [38] compared the effectiveness of SAGAT, online detection, SART, and observer scoring techniques in a simulated experiment involving 10 experienced air traffic controllers to determine which method best influenced the controllers' SA. Willems and Heiney [15] utilized SAGAT to assess the controllers' SA response to airspace sector queries. Their findings revealed that only 20% of the correct responses were specific to the layout of the aircraft. Furthermore, SA decreased as task load increased, particularly for data-related tasks compared to radar-related tasks. Similarly, in the field of ATC, Kaber et al. [39] reported significant differences in Level 1 SA in different automation modes with information acquisition resulting in the highest SA and action execution resulting in the lowest SA. Sethumandhavan [40] conducted a study using four levels of automation (information acquisition, information analysis, decision-making, action selection and action execution automation) and measured SA before and after automation failure using SAGAT. The findings indicated that SA was significantly higher in the information analysis automation condition compared to the other three automation conditions. Additionally, participants' SA before automation failure was significantly higher than their SA after the failure occurred.

Designing appropriate and effective queries is crucial, and the SAGAT query should incorporate three phases of situational awareness [41]. When ATCos are questioned, queries can be formulated in various ways. For example, perception-related questions may be used, where controllers are asked about their perception of the situation, such as "How many aircraft are currently approaching the airport?" Comprehension-related questions assess the controllers' understanding of the situation, for instance, by asking them, "In which quadrant of the screen are the majority of the aircraft that you have control over located?" Finally, forecasting-related questions test the controllers' ability to predict future events, such as "In which quadrant of the screen is the aircraft expected to land?" The controllers' responses to these questions are recorded, and the accuracy of their responses is evaluated as a measure of their situational awareness.

2) SART

Taylor et al. [42] conducted a study that revealed significant differences between 3D (three-dimensional) and 10D (ten-dimensional) Situation Awareness Rating Technique (SART) ratings in ATC missions.

3) SPAM

In another study by Strybel et al. [43], the Situation Present Assessment Method (SPAM) was used to compare the situational awareness of retired ATCos when employing separation and spacing techniques in airway and transition areas. The study revealed that situational awareness was highest in the airway sector when controllers were responsible for interval assurance and when intervals were automatically managed.

4) AI-based SA measurement techniques

The development of Unmanned Traffic Management (UTM) and Advanced Air Mobility (AAM) programs led by organizations such as SESAR, FAA and NASA has advanced the application of new mathematical algorithms and system implementations in air traffic control [29], [44]. These programs aim to take advantage of AI techniques to achieve higher levels of automation and improve air traffic management capabilities beyond current limitations. In the field of Air Traffic Management (ATM), AI-based SA testing and enhancement techniques have been successfully implemented and applied in SESAR projects such as AISA, ARTIMATION, MAHALO, and TAPAS [29]. These techniques have been utilized in various aspects of ATMs, including control operations security, intelligent assisted decision-making, and conflict detection and resolution. The impact of these new technologies and systems on the assessment of situational awareness of the controller is significant. They offer improved functionality, increased efficiency, and enhanced decision-making support for air traffic controllers. These AI-based systems work by using advanced algorithms and machine learning models to process large amounts of data and provide real-time insights and predictions to controllers. Overall, the integration of AI techniques and advanced technologies into air traffic control holds great potential to advance the assessment of controller situational awareness, providing controllers with valuable tools and support to ensure safe and efficient air traffic management.

(1) The SESAR AISA project focuses on enabling safe sharing of SA between humans and AI in ATM. The project developed an intelligent SA-aware system that combined KG, an inference engine, and ML techniques. Through a “human-in-the-loop” simulation, the project aimed to establish a mechanism for sharing the same SA between ATM team members and AI. The objective was to create a system where an AI component could reach the same conclusions as an ATCo when faced with the same problem, while also being able to provide explanations for its decisions. This collaborative SA approach aimed to enhance the overall performance and decision-making capabilities of the ATM team.

Figure 3 illustrates the concept of distributed SA in a human-automated setting for future AI-based automated systems. Integration of AI and digitalization opens up new possibilities to improve air traffic control safety. It enables better identification of potential risks and early detection of subtle signs of incidents through analysis of ATC big data, including information from written reports that were previously difficult to standardize. Using digital technologies and AI, future systems can be designed and operated with a more comprehensive understanding of their behavior. Historical data can be used to model the performance and interactions of these systems, leading to more robust designs and safer operations.

In summary, the development of digitalization and AI in air traffic control offers opportunities to enhance safety by facilitating the sharing of SA between humans and automated

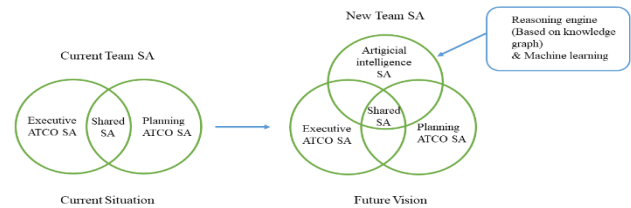


FIGURE 3. Distributed SA concepts for future automated systems (adapted from the SESAR AISA project).

systems. This collaborative approach, supported by advanced technologies, has the potential to improve risk assessment, early incident detection, and the overall effectiveness of air traffic management.

(2) The ARTIMATION project, known as Transparent Artificial Intelligence and Automation to Air Traffic Management Systems, focuses on addressing the challenges related to transparency in automated systems used in air traffic management. The project aims to develop interpretable AI models that can provide insight into the decision-making processes of these systems. One of the key aspects of the project is the integration of different levels of interpretation into an adaptive passive brain-computer interface. This integration allows adaptation to the contextual interpretability needs of ATCos and considers their mental and emotional states, which can be measured through neurophysiology. By incorporating interpretable AI and adaptive interfaces, the ARTIMATION project aims to enhance the transparency of ATM automated systems. This transparency enables ATCos to better understand the reasoning behind the decisions made by these systems. It also facilitates effective collaboration between humans and AI, allowing ATCos to maintain SA and make informed decisions.

(3) The MAHALO project, short for Modern ATM via Human/Automation Learning Optimization, focuses on the development of a hybrid machine learning system for air traffic management. This system incorporates layered deep learning and reinforcement learning models, along with innovative interface methods, to evaluate various aspects such as ML consistency, transparency, and traffic complexity. One of the key objectives of the MAHALO project is to assess the impact of ML on important factors such as SA, trust, workload, and relative performance of ATCos in real-time simulations. To achieve this, the project uses novel techniques, including the use of solution space graph metrics as input to ML agents. Using layered deep learning and reinforcement learning models, the system can learn from the data and optimize its performance over time. Innovative interface methods utilized in the project provide a means of effectively analyzing the consistency and transparency of the ML system, while also considering the complexity of air traffic. Real-time simulations are carried out to evaluate the performance of the

system's and its impact on various aspects of ATM operations.

(4) The TAPAS project, Towards an Automated and Explainable ATM System, focuses on exploring highly automated scenarios in air traffic management through the use of interpretable artificial intelligence prototyping and Visual Analytics (VA) techniques. The main objective of the project is to identify the key factors that contribute to the trust of AI in ATM operations. One of the key challenges in implementing highly automated systems in ATM is ensuring safety and security while maintaining transparency and interpretability. The project utilizes interpretable AI prototyping to develop AI models that are transparent and explainable in their decision-making process. Using these models, the project aims to gain insight into the factors that influence AI trust in ATM operations.

(5) Effective fusion of multidimensional scenario information in a controlled environment has posed a challenge to maintaining situational awareness among air traffic controllers and pilots. To address this issue, Carlos et al. [45] proposed the ATM Reasoner approach of the Situational Awareness Decision Support System (SAWDAR), which employs an ontological information and semantic reasoning approach to support the decision-making process in air traffic management.

The SAWDAR approach aims to improve increase airspace awareness by analyzing contextual concepts and their relationships, including elements such as aircraft, airports, surveillance radars and associated operators. In scenarios where an aircraft is preparing to take off while Unmanned Aerial Vehicles (UAVs) are present, potentially posing a flight risk, the SAWDAR approach alleviates the workload of controllers and pilots by offering decision recommendations that aid their mental processes and fulfill the needs of ATM.

Although ontologies for future ATM systems are being considered in the SESAR project [29], there is a scarcity of studies using ontologies to support flight decision-making in aviation. The ontology-based SAWDAR approach serves as a valuable guide for the advancement of ATM technology toward autonomy. Integrating ontological information and semantic reasoning facilitates more efficient and informed decision-making, ultimately enhancing SA and reducing the cognitive burden on human operators.

D. SUMMARY

In this section, we provide a summary of the typical SA measures from both individual and team perspectives. We also analyze the fundamentals, application scenarios, advantages, and disadvantages of each approach. Particularly for ATCos' SA, we introduce four main measurement techniques. After a detailed introduction and application analysis of these methods, we can conclude that SAGAT is still the most widely used technique with high sensitivity, reliability, and predictability among traditional SA measurement methods, regardless of whether it is individual or team SA measurement.

SART has been extensively employed in the area of air traffic control and is especially suitable for assessing situa-

tional awareness in situations with varying traffic densities and in a variety of conflict detection automation scenarios. Additionally, CAST is an effective technique to evaluate the SA of a team, combining the flexibility of the team to adapt to dynamic environments with the process of achieving a higher SA of the team in an efficient manner.

The emergence of AI technology has significantly broadened the scope of SA measurement methods. By combining semantic web and ontology information fusion techniques, multisource information data fusion methods, and machine learning methods, the accuracy and completeness of SA measurements can be improved, thus improving the team SA. In the field of ATC, the UTM, and AAM programs have encouraged the use of new mathematical algorithms and system implementations. Consequently, ATCos' SA measurements are now more likely to use advanced algorithms and machine learning models to process large amounts of data in order to provide more precise and predicted measurements.

III. ATCO'S SA BASED ON NEUROPHYSIOLOGICAL MEASUREMENTS

The measurement of physiological indices, such as eye movement and EEG techniques, has been mentioned in Section II-A3. These techniques offer the advantage of objectively and accurately measuring SA. Furthermore, data recorded of eye movement and EEG provide information on the neurophysiological characteristics of the individuals, shedding light on the physiological mechanisms underlying cognition, emotion, volition, and behavior. This knowledge helps us to understand the abstract nature of the human mind. As the field of artificial intelligence has advanced, machine learning techniques applied to eye movement and EEG data have gained popularity among researchers. Both eye movement and EEG have shown exceptional performance in monitoring the state of controllers in ATC, including aspects such as emotion, fatigue, and workload. In this section, we will discuss the specific details of these two techniques, comparing their performance, advantages, practical applications, and potential uses in the measurement controllers' SA.

A. EYE MOVEMENT

Eye movement techniques were initially used in neurophysiological experiments. The technology is based on the capture and extraction of information about the characteristics of the eyes, using the physiological structure of the eye to measure eye movements and estimate visual direction or gaze location. Consequently, eye movement measurements can capture user emotions and offer real-time, accurate recordings of changes in eye movement when observing scene information. For humans, eyes are the primary means of perceiving, understanding, and comprehending information about the external world. In the context of ATCos, low SA is often associated with a limited amount of useful information retrieved through the behavior of eye movement. This limitation can impact control judgments and decision making, and pose potential risks to the safe and efficient execution of tasks. Therefore,

the relationship between changes in attention allocation and SA levels in ATCos can be analyzed using eye movement metrics.

Common metrics used for eye movement measurements include blink frequency, pupil diameter, and gaze metrics. Analyzing eye movement data can be presented through gaze trajectory maps and hotspot maps. However, obtaining accurate information about the observed interface during blinking is challenging, and the main stage of information acquisition occurs during gaze. Gaze metrics can be further divided into metrics such as the gaze time of the first gaze point, dwell time of a single gaze, the total number of gazes within the area of interest, Nearest Neighbor Index (NNI), gaze entropy rate value, and the number of gaze points within the interest area. These gaze metrics capture the gaze behavior of the eye movement to acquire information and analyze changes in attention allocation, thus quantifying the operator's SA. Studies focusing on gaze metrics have demonstrated that gaze time and gaze frequency impact information acquisition in SA1, while gaze entropy affects the acquisition of new information in SA3.

Eye movement techniques have made significant contributions to the study of controller SA. Researchers have recognized that eye movement data can effectively reflect visual attention characteristics and serve as a reliable indicator to study attention allocation. Wickens [46] emphasized the value of eye movement data in reflecting visual attention and its potential as an indicator for studying attention allocation. DiStasi et al. [47] demonstrated the feasibility of using eye movement-derived attention indicators to detect early fatigue in controllers. They showed that changes in attention allocation can be detected through eye movement patterns. Furthermore, Wang et al [48] looked into the distinctions in eye movement characteristics among various air traffic controllers. Collectively, these studies demonstrate the value of eye movement techniques in understanding and analyzing attention allocation, workload effects, fatigue detection, and skill-related variations in controller SA. Integration of eye movement technology with deep learning and machine learning has opened up new possibilities in the field. Researchers have explored the feasibility of combining eye feature information with automation and assessing the resulting impact on SA operator SA [49]. This approach aims to analyze changes in SA by incorporating eye movement data into automated systems. Overall, the development of ML-based models for the identification and prediction of SA in controllers represents a promising direction. Using eye movement data and advanced ML techniques, these models can assist to quickly identify and predict SA levels, ultimately contributing to the maintenance of optimal SA in air traffic control.

B. ELECTROENCEPHALOGRAPHY

Physiological indicators such as EEG, ElectroCardioGram (ECG) and skin conductivity are commonly used to assess the physiological status of individuals. EEG, specifically, captures the spontaneous and rhythmic electrical activity of brain

cell populations and can be visualized in various forms such as waveforms(a), power spectra(b), spectral topography(c) and thermograms(d) (refer to Figure 4). EEG signals can be decomposed into four basic rhythms: delta, theta, alpha and beta. These wave signals provide information on the different levels of fatigue experienced by individuals. The advantage of EEG technology lies in its ability to directly record the electrical activity of the cerebral cortex, providing objective data on cognitive, emotional and fatigue levels through four-wave signals. Traditionally, SA measurement has relied on the assessment of fatigue and emotion based on these wave signals. Commonly used EEG index parameters include relative power, wavelet entropy, scale entropy, and alignment entropy [21].

Figure 5 illustrates the relationship between eye movement and EEG indicators and controllers' SA. These indicators, when combined, provide valuable information on the cognitive and physiological states of controllers, contributing to the assessment and understanding of their SA levels.

C. SUMMARY

In this section, we discuss the advantages of eye movement and EEG techniques as physiological indicators for assessing the state of air traffic controllers in terms of situation awareness. We have provided studies on physiological metrics in Section II, and here we compare in more detail the performance, advantages, practical applications, and potential applications of the two physiological metrics, eye movement and EEG techniques, in the measurement controllers' SA.

We studied previous research to determine that eye movement and EEG techniques are dependable and consistent in examining controller attention distribution, workload effects, fatigue detection, and evaluating controllers' SA. In particular, the measurement of physiological metrics can be combined with machine learning and deep learning to further investigate the connection between eye feature data, EEG metric parameters and the cognitive and physiological states of controllers. This combination could give a more precise assessment and understanding of the controllers' SA level.

In conclusion, eye movement and EEG measurements have proven to be highly effective in assessing the situation awareness of controllers. By combining these techniques with machine learning and deep learning, we can better understand the cognitive and physiological states of the controllers. This research is a valuable resource to improve awareness of the situation and the performance of ATCos.

IV. SENSITIVITY ANALYSIS OF FACTORS AFFECTING SA

Evaluation of SA is not a singular concept; it requires a multidimensional analysis to achieve a scientific and accurate assessment. SA measurement technology is just one aspect that influences the accuracy and superiority of SA evaluation. Another crucial factor is sensitivity, which refers to the factors that significantly impact SA and how they are changing with the increasing prevalence of automation. This article considers existing research on factors that affect SA and proposes

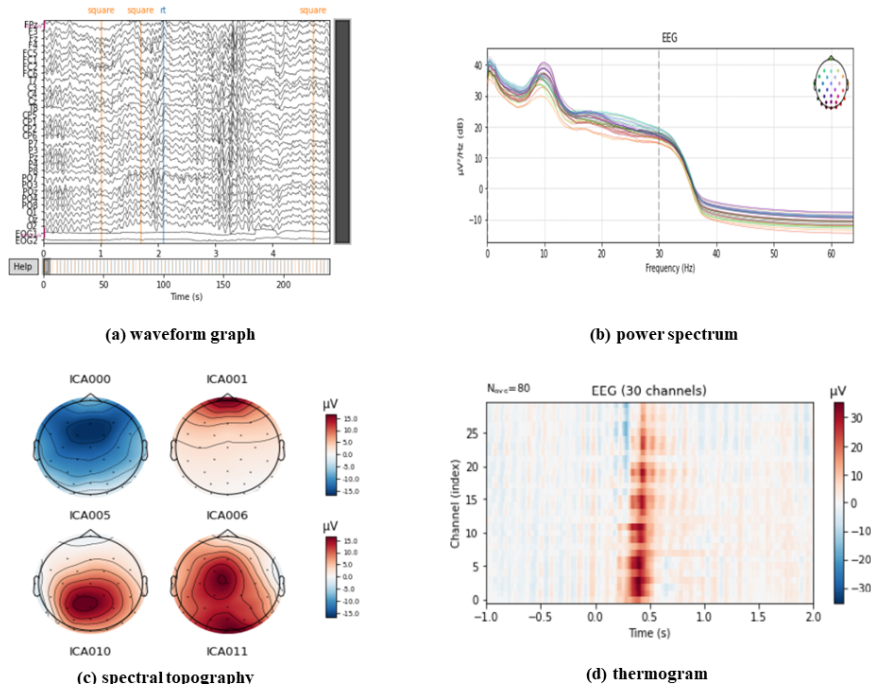


FIGURE 4. Analysis of EEG data in four forms.

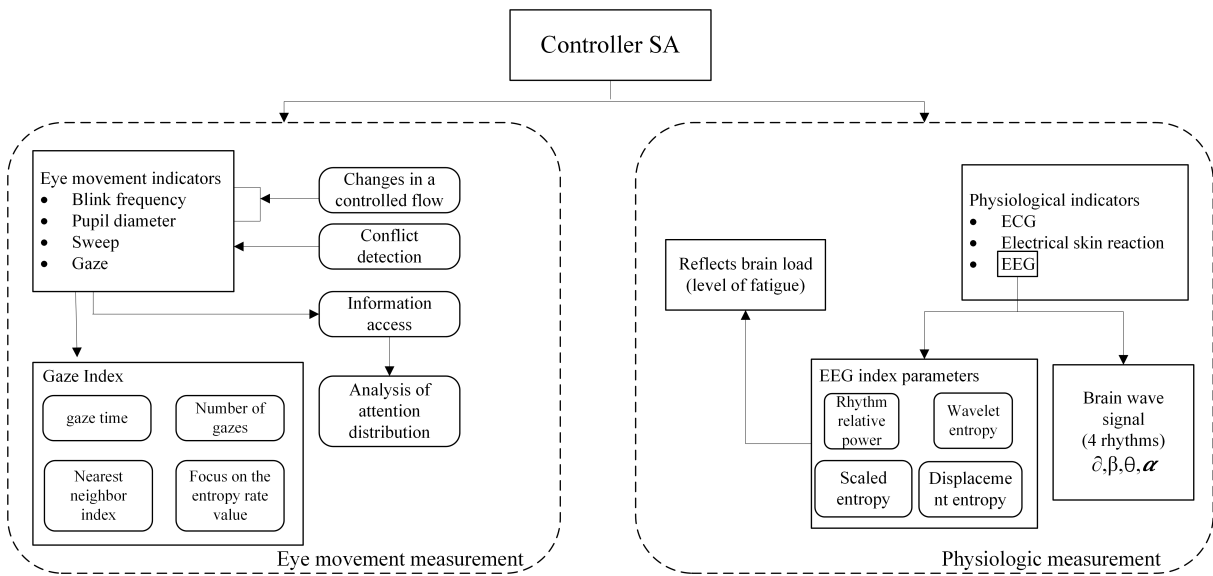


FIGURE 5. Application of neurophysiological measurement in the controller SA.

four categories of sensitivity factors that predominantly influence SA today. Figure 6 illustrates these four categories of sensitivity factors and their relationship with the ATCOs' SA.

A. WORKLOAD

The amount of work air traffic controllers (ATCOs) must handle is essential to maintain the safety of air traffic. The impact of this workload on ATCOs is mainly seen in the mental strain it places on them. [50]–[52]. The manifestation of fatigue is usually reported in the form of the frequency of

failed subtasks, which is expressed as a fatigue index. Feng et al. [53] studied the connection between mental workload and situation awareness (SA) using the SAGAT method. The results showed a strong correlation between mental workload and attention allocation efficiency and attention allocation mode, with SA being higher at low mental workload than at high workload. Furthermore, a high-fidelity, human-in-the-loop air traffic control simulation experiment demonstrated the presence of an interaction between workload and SA for different automation levels [54]. Examining the relationship

between the SA of future ATCOs and various factors, such as load and fatigue, provides helpful and predictive guidance on when automation should be used most effectively.

B. PERFORMANCE

SA and job performance have a reciprocal relationship, where high levels of SA contribute to effective decision making and the maintenance of high levels of performance. Performance in the control domain is typically measured by factors such as response time and correctness [5]. Research conducted in the field of ATC has revealed a significant correlation between ATC performance and SA questionnaire scores [55]. In the case of off-line SA questionnaires, experienced subjects demonstrated a strong correlation between SA and performance, whereas inexperienced subjects exhibited lower scores on the questionnaire. The use of cues during tasks also showed a correlation with performance and SA. Effective use of cues, along with accurate and rapid identification of task stimuli, resulted in superior response performance and higher SA scores.

C. WORKING MEMORY

Working memory plays a crucial role in reflecting the precision of reporting SA problems by capturing attentional control and facilitating the identification of SA problems [56]. It encompasses long-term, short-term, and operational memory. Long-term and short-term memory are associated with experience and correspond to two categories of individuals: experts and novices, respectively. Inexperienced operators often face limitations in their SA due to constraints in working memory capacity [55]. On the other hand, operational memory is more focused on cue-based associative cognition and interaction with the operational environment [57]. As individuals acquire higher levels of expertise in a specific domain, they tend to rely more on operational memory to actively update and process new information as the task progresses, rather than relying solely on passive working memory.

D. THE AUTOMATION

The rapid advancement of automation has led to a reduction in human agency as more operations are taken over by automated systems. This trend poses challenges to humans in terms of understanding scenarios and the intent of the system, which is undesirable. Therefore, the level of automation becomes a critical factor that influences SA in both the present and the future contexts. Air traffic controllers face the challenge of handling numerous tasks on a daily basis. Although automation in air traffic management can enhance efficiency, such tools must be completely reliable to effectively support controllers in their work. An intelligent system equipped with SA capabilities can provide the necessary framework for the safe development of machine learning tools.

Several SESAR projects, such as the AISA project, have assessed the feasibility of integrating a manual SA mechanism into team SA. Additionally, the HAAWAI project has developed a new ML-based speech recognition framework to

aid controller decision making. Many other SESAR projects, including MAHALO, TAPAS, and ARTIMA-TION, are focused on ensuring that AI-driven solutions are interpretable, transparent, and trustworthy. These projects also emphasize the protection of private datasets used in ML applications to encourage data sharing, as demonstrated by the AICHAIN project.

The level of automation in air traffic management encompasses several key aspects: automation phase, automation system, system transparency, and automation trust.

1) Automation phase

The automation phase involves four components: information acquisition, information analysis, decision selection and execution, and automation execution. The SAGAT technique has been used to measure SA before and after automation failures, allowing the assessment of SA changes.

2) Automation system

Automated systems can be categorized into three levels: manual, semi-automatic, and fully automated with auxiliary systems. The complexity of automation is closely related to mental workload, performance and SA. As the level of automation increases, the demands on controllers change, which can impact their SA.

3) System transparency

The design of the transparency of the control automation system includes factors such as information visualization (presenting air, ground and space data), effective information accuracy (classifying importance levels), prioritization of information quantity and the presence of auxiliary systems to support the maintenance of good SA and prevent complacency or excessive mental workload.

Although AI can assist with various control tasks, the underlying algorithms often lack transparency, particularly in techniques such as neural networks and deep learning. Lack of transparency can have a significant impact on trust in air traffic management. Therefore, as technologies like machine learning, vision, and text analytics continue to advance, information visualization in aviation needs to be prominent. Visual warnings, for example, tend to be more effective than auditory or integrated interface warnings in capturing operator' attention. Furthermore, the ongoing development of big data processing, including machine learning and visual and text analytics, will provide air traffic controllers and pilots with a better understanding of environmental information such as weather conditions, airspace/airports, and aircraft movements during take-off and landing.

4) Automation trust

Trust in automation plays a crucial role in SA. Subjects with high levels of trust in automation tend to become more complacent, which can have a negative impact on SA. In recent years, the concept of "Human-Centered Artificial Intelligence" (HCAI) has emerged as an academic perspective

and research direction. HCAI prioritizes humans in the design of systems, tools, and agents, in order to support goals such as self-efficacy and improve SA by improving human performance. In the context of HCAI, designers strive to improve trust and reliability by developing highly automated systems that are human-centered. This involves designing interactive interfaces and control panels that allow users to better understand the state and behavior of the machine over different timeframes such as 10, 80, or 800 seconds. The goal is to enable for a high degree of human control along with a high degree of computer automation. Additionally, it is essential to establish standardized and secure certified governance. This includes reliable software systems, robust management mechanisms, credible external review and certification processes, and governance regulations. As the level of automation continues to evolve, it is crucial to pay attention to factors related to automation trust and study their relationship with SA. Understanding this relationship can help maintain a good level of SA in human-centered automated systems.

E. SUMMARY

This section emphasizes the significance of a multidimensional approach for accurately and scientifically evaluating ATCOs' SA. The assessment of SA is a process-based, ever-changing, and uncertain analytical process and thus necessitates the combination of multiple factors. Sections II and III focus on the technical aspects of measurement to assess controllers' SA, while this section focuses on another essential dimension of SA assessment, namely the four types of sensitivity factors that affect SA. These categories are environmental, cognitive, physical, and emotional.

The level of automation is having a growing influence on the assessment of situation awareness. As automation is becoming a major factor in the present and future of air traffic control, intelligent systems with the capacity to evaluate SA can provide the necessary structure for the secure use of machine learning tools. Artificial intelligence can help controllers with a variety of tasks, but the use of intelligent systems must be understandable, clear, and reliable for controllers to maintain good SA, more accurately comprehend and evaluate actual operational circumstances, and make safe and effective decisions.

In conclusion, a thorough evaluation of ATCOs' Situational Awareness can be accomplished by taking into account a variety of elements, such as measurement techniques and factors that influence SA. In the face of growing automation, intelligent systems can provide a platform for machine learning tools and guarantee that they are understandable, clear and reliable in order to maintain a satisfactory level of SA of controllers and thus make precise and secure decisions in actual operations.

V. DISCUSSION

The objective of this article is to provide a survey on the fundamentals and sensitivity of Situational Awareness (SA) in air traffic control. Modern air traffic control is heavily

reliant on complex technical and automated systems, making it essential to accurately assess ATCOs' SA to guarantee air traffic safety and efficiency. This study seeks to bridge the gap in SA assessment and provide a basis for future developments in the field. The Introduction section of the paper emphasizes the importance of this research and the need for ATCOs to work with automation systems. These automatons not only help ATCOs in their duties, but also have an effect on their SA. We also identify in the paper that factors such as interpretability, transparency, and trustworthiness are essential for the successful implementation of automation systems. These factors have a direct influence on whether ATCOs rely on the instructions and recommendations of the system, which, in turn, affects the accuracy and timeliness of SA.

A. APPLICATION OF ADVANCED TECHNOLOGY IN AIR TRAFFIC CONTROL

Automation is a major factor affecting the safety of air traffic operations. To obtain an accurate and reliable assessment of ATCO SA, however, we must take into account a variety of factors, such as the scale and sensitivity of the measurement techniques. In Section II, we discuss the main SA measurement techniques, particularly those involving artificial intelligence. Section III further highlights novel and potentially beneficial eye tracking and EEG techniques. By combining these techniques, we can gain a more comprehensive understanding of the assessment results and help controllers make better decisions.

B. POTENTIAL IMPACTS AND FUTURE PERSPECTIVES

This paper examines the potential impact of this research on air traffic control practice. We suggest that it could lead to increased controller productivity, fewer mistakes in decision-making, and improved flight safety. Moreover, our research may be of use to policymakers and training organizations in addressing future technological and automation issues. We acknowledge that this study is only a beginning and that further research is needed to enhance the accuracy and sensitivity of situation awareness assessments to promote the use of intelligent systems in air traffic control. We recognize the importance of advanced technologies in air traffic control and are committed to further exploring their applications and potential effects in future studies to advance the industry and the safety of flight.

VI. CONCLUSION

This review explores in depth the theoretical development of individual and team SA and provides a comprehensive overview of the main measurement methods. Although SAGAT and SART methods are widely used in SA measurement, we also identified some limitations and challenges.

With the rapid development of artificial intelligence technology, new SA measurement methods continue to emerge, including SA enhancement technology based on ML, fusion method using semantic network and ontology information, method combining inference engine and knowledge

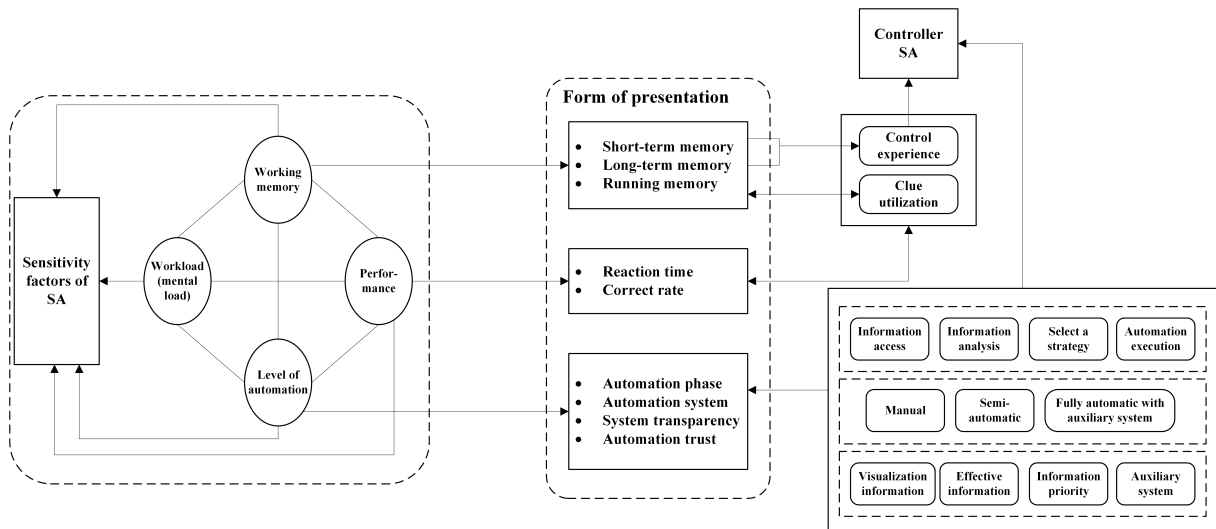


FIGURE 6. Four types of sensitivity factors and their relationship to controller SA.

graph, and multi-source information data fusion method. The SESAR/NextGen research project clearly highlights the importance of these new measurement methods, providing valuable guidance for the future of complex air traffic management, and promoting further development of safety, efficiency, and intelligence.

In addition, we analyzed and compared the advantages, applications, and potential applications of eye movement and EEG techniques in the measurement of controllers' SA. The workload is an important factor affecting controllers' SA and future research can focus on how to effectively reduce workload while maintaining good SA in air traffic management intelligent systems. The level of automation is also a key factor for the present and future, as automation of air traffic management can improve efficiency, but it must be ensured that these tools are completely reliable to properly assist the work of controllers. Future research should also focus on exploring team SA mechanisms to build trust for optimal human-machine interaction.

While significant progress has been made in SA research, there are still some key issues and directions that need to be further explored:

(1) Challenges in SA measurement techniques: Existing SA measurement techniques, including widely used methods such as SAGAT, face some challenges in practical applications. Future research will require further development of new algorithms to effectively address these challenges, particularly with regard to "freeze" detection.

(2) Personalized assessment model: In view of individual differences, we need to focus on the study of the personalized SA assessment model. Combining eye movement and EEG technology with individual physiological information, such as facial analysis, enables a more accurate and targeted SA assessment.

(3) The complexity of human-machine collaboration: As the level of automation increases, the effectiveness of human-

machine collaboration becomes more and more important. In teamwork involving automated machines, such as critical dynamic communication between operators, between operators and machines, and between machines, issues arise related to shared SA, human-machine trust and transparency design. Therefore, an in-depth study of SA under human-machine collaboration is essential to better understand and address these challenges.

In conclusion, we are particularly grateful to the individuals, organizations, and institutions that have provided support and assistance during the course of this study. While we have provided a comprehensive overview of advanced SA technologies and research, we also encourage future research to delve further into these areas to address practical limitations and provide more opportunities for SA applications in various fields to provide safer, more efficient, and intelligent solutions for future air traffic management.

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