

Article

Comprehensive Evaluation of Remote Tower Controllers' Situation Awareness Level Based on the Entropy Weight Method (EWM)–TOPSIS–Gray Relational Analysis Model

Tingting Lu, Miao Hao * and Zhaoning Zhang

School of Air Traffic Management, Civil Aviation University of China, Tianjin 300000, China; ttlu@cauc.edu.cn (T.L.); zzhaoning@263.net (Z.Z.)

* Correspondence: 2022031039@cauc.edu.cn

Abstract: In recent years, the rapid development of remote tower technology has made it crucial to accurately assess the situational awareness (SA) levels of remote tower controllers. Such an assessment is significant for controller training and remote tower system design. This study employed the SART scale to compare controllers' SA scores in traditional and remote tower environments. Results revealed significant differences, especially in attention demand and situational understanding. Subsequently, a quantitative analysis of controllers' perception, understanding, and decision-making abilities was conducted, integrating subjective and objective data. Eye-tracking, heart rate, working memory scales, and communication-coordination scales showed significant results. Experienced controllers had better psychological safety skills, while trainees were more likely to increase vigilance. Moreover, a series of sensitive SA indicators were identified. An evaluation index system was established using the entropy weight method. By calculating the Euclidean distance, Gray relational degree, and comprehensive proximity coefficient, the SA levels of controllers were comprehensively evaluated. The top five important indicators were average blink rate, scan length, average fixation duration, fixation duration, and average pupil diameter. These findings support enhancing air traffic control safety and refining SA assessment for remote tower controllers.



Academic Editor: Carla Raffaelli

Received: 15 December 2024

Revised: 24 February 2025

Accepted: 24 February 2025

Published: 28 February 2025

Citation: Lu, T.; Hao, M.; Zhang, Z. Comprehensive Evaluation of Remote Tower Controllers' Situation Awareness Level Based on the Entropy Weight Method (EWM)–TOPSIS–Gray Relational Analysis Model. *Appl. Sci.* **2025**, *15*, 2623. <https://doi.org/10.3390/app15052623>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: controllers; situation awareness; remote tower; EWM–TOPSIS–Gray relational analysis model; comprehensive evaluation

1. Introduction

In recent years, remote tower technology has advanced swiftly, both nationally and globally, as a novel element of air traffic control (ATC) systems. In contrast to conventional towers, remote tower controllers often operate from distant control centers, using high-definition digital cameras, meteorological sensors, and audio-visual systems. These systems relay real-time video, audio, and other data signals to a centralized control center, facilitating the remote command and control of aircraft. This system enables the seamless integration of several high-definition video feeds over extensive regions, thereby enhancing the efficiency and safety of air traffic control [1,2].

European nations have been pioneers in remote tower research. In 2014, the Single European Sky ATM Research (SESAR) program initiated several extensive air traffic management demonstration projects. These projects investigated the feasibility of a single remote tower servicing multiple airports, thereby laying the groundwork for the practical implementation of remote tower technology [3]. Josefsson B. et al. suggested an optimized

framework for remote towers, developing an automated staff scheduling system that tackled real-world flight schedule difficulties and offered optimum shift allocation for five Swedish airports [4]. As remote tower technology is increasingly used in Europe, including remote apron control, single-mode or multi-mode operations, and emergency backup systems, major airports globally have begun operational validation of remote towers [5,6].

The advancement of distant towers in China has begun comparatively late. Recently, airports such as Guangzhou Baiyun, Xinjiang Nalati, and Zhejiang Low-altitude Flying Center have been progressing with remote tower initiatives. Given the topographical limitations in some rural regions of China, where a deficiency of air traffic controllers may occur, remote tower technology is especially appropriate for small airports in these undeveloped locales. Consequently, investigating remote tower technology in China is quite significant.

Controllers at remote towers generally interact with pilots via computer displays and communication devices, whereas conventional tower controllers function directly from airport towers, allowing them to see aircraft and the airport environment in real time. Hollan et al. said that the differences in how air traffic is managed between physical towers that are far away and those that are closer to people need to be carefully looked at and tested to make sure that controllers in remote towers have the right cognitive skills [7]. Peter Kearney and associates used the Human Error Template (HET) and employed NASA-TLX to analyze workload disparities between conventional physical towers and numerous remote towers. Their research revealed substantial disparities in psychological demands, temporal demands, effort, and degrees of discontent between the two operational types [8]. Lu Tingting et al. examined disparities in workload, attention distribution, and situational awareness between remote and conventional tower controllers from an ergonomic standpoint, using the Qiandao Lake General Airport Tower as a case study. They formulated safety operation evaluation guidelines for remote towers, serving as a benchmark for assessing the safety of remote tower technology [9].

Conceptually, situational awareness (SA) is a cognitive process encompassing an individual's whole range of actions, comprising the observation, comprehension, and anticipation of changes in the surrounding environment within a defined temporal and spatial context [10]. The digitalized operational techniques of remote tower controllers necessitate reliance on communication, navigation, and surveillance systems, confining them to specialized, stationary environments. Moreover, controllers must concentrate on displays for prolonged durations, often in a stationary posture, with little sensory engagement, which may easily result in tiredness [11]. Research demonstrates that the situational awareness level of remote tower controllers directly influences the safety and efficiency of the air traffic control operations [12]. Mitigating and minimizing situation awareness-related mistakes in remote tower operations, together with enhancing human dependability, are essential for guaranteeing the safe functioning of remote towers. Researchers from the German Aerospace Center (DLR) used questionnaire surveys [13] and on-site validations [14] to look at how situational awareness, operational methods, and system usability changed when the equipment and workstations were changed. Utilizing these methodologies, they investigated the alterations in situational awareness and perceptual capacities of distant tower controllers under various traffic conditions. Controllers must sustain situational awareness throughout operations to identify dynamic targets, including aircraft, ground vehicles, and dangers like birds. The most efficient approach to enhance air traffic control capabilities and safety is through efficient performance monitoring [15].

Effective situational awareness in controllers can guarantee the secure and effective functioning of air traffic control. Nonetheless, a reduction or loss of a controller's situational awareness may result in perilous circumstances, such as aircraft delays or air traffic conges-

tion, with potentially catastrophic repercussions. Consequently, it is essential to accurately identify and evaluate the situational awareness levels of remote tower controllers.

1.1. Mechanism Analysis of Situation Awareness Loss in Remote Tower Controllers

Endsley [15] first presented the concept of situation awareness (SA), defining an extensive SA model that outlined the interplay between people and automation, along with the various aspects that influence this interaction. In this method, perception, understanding, and projection are the fundamental elements of situational awareness (SA).

Perception is the first stage in attaining situational awareness. It entails identifying the conditions, characteristics, and pertinent components of the environment and establishing a basis for later phases of understanding and forecasting. Blaylock's study demonstrated that people's risk perception increases with an increase in danger levels [12]. In remote tower control operations, controllers reach the perception phase of situational awareness by keeping an eye on changes in interface components and physiological signals like heart rate variability.

The comprehension phase is the cognitive process that follows information perception, with the objective of grasping the significance of pertinent items [16]. Hartman and colleagues discovered that as controllers' knowledge and experience increase, their situational awareness increases. Even with inadequate information, seasoned controllers may discern probable correlations among data points [17]. Consequently, the understanding phase is significantly dependent on the considerable work experience of controllers. The cognitive processes of the preceding two phases form the foundation of the projection phase. Controllers use this information to anticipate fluctuations in air traffic during a certain duration, consequently impacting their ensuing decision making. The three stages of SA intertwine, with the successful completion of one level serving as a prerequisite for the next stage [18].

Remote tower controllers must accumulate information from the human-machine environment pertinent to their jobs or work goals, thereby enhancing situational awareness over time. Furthermore, this state information may vary across geographical dimensions. In summary, situational awareness is an essential precondition for controllers' decision-making processes, directly impacting their choices. Controllers with elevated situational awareness can effectively evaluate the present circumstances and make optimum judgments, while those with diminished situational awareness are susceptible to misinterpreting the environment, resulting in erroneous decisions.

1.2. Research on Situation Awareness Indicators

Researchers have conducted comprehensive studies on the impact of eye movement markers on situational awareness (SA). Koen et al. [19] looked at pilots' situational awareness (SA) using markers like fixation frequency, fixation length, and saccade entropy. They wanted to see if eye movement could be used as a way to measure SA. According to Fidopiastis et al. [20] used NNI analysis to look into how drone operators' eye movements change when they are performing different tasks. They looked at how automation and workload affect eye movement strategies. Liang et al. [21] used eye-tracking technology to examine changes in drivers' situational awareness throughout the takeover process in autonomous driving. Lafond and D. found that controllers' ability to visually search is important for staying aware of what's going on in both radar displays and airport control towers. How they focus their attention is greatly affected by things like the layout of their workstations, the environment, the system equipment, and the design of the human-machine interface. To thoroughly comprehend the influence of various designs on cognitive function, it is essential to use a holistic strategy that encompasses the assessment of human performance in distant towers [22].

Wen-Chin Li et al. used eye-tracking technology to document and evaluate the visual scanning behaviors of remote tower controllers over 32 situations, evaluating the efficacy of operating numerous distant towers. The investigation revealed a strong correlation between controllers' visual scanning behaviors and work stress. Controllers overseeing various monitoring activities at a single distant tower exhibited significant challenges in human-machine interaction, particularly influenced by information presentation, job complexity, and operating environment [23]. Aviation traffic control (ATC) is a career defined by significant pressure due to the real-time, dynamic management of aviation traffic [24]. Individual situational awareness, behavioral states, and psychological activities often correlate, leading to extensive discussions about the use of heart rate variability indicators to assess fatigue or situational awareness among personnel. Wilson [25] suggested using physiological indicators such as electroencephalogram (EEG), blinking, cardiac activity, event-related potentials (ERP), instantaneous heart rate, and electrodermal activity (EDA) to gauge operators' situational awareness (SA) levels. Yang Yue et al. performed research by gathering eye movement and electrocardiographic data from controllers, using multifactorial variance analysis to investigate the impacts of various complexity elements and physiological alterations in subjects [26]. They used three machine learning methods to evaluate the cognitive burden of participants. Li Yanhui [27] used the LF/HF ratio in heart rate variability to illustrate the influence of weariness on the autonomic nervous system of drivers on plateau roads. Sun Houjie et al. used a three-factor variance analysis to examine the impact of long-term working memory and attention allocation on the situational awareness of armored vehicle crew members. The results showed that 3D-SART, SAGAT, aberrant information response time, eyelid opening, gaze time ratio in the instrument region, SDNN, and PNN50 were very good at showing changes in SA levels [28]. Controllers experiencing excessive workload or adverse mental conditions, such as weariness or attention, often struggle to sustain adequate situational awareness and may commit significant mistakes [29]. Consequently, recognizing and examining human aspects associated with controllers' situational awareness is essential for mitigating hazardous situations and enhancing the safety and efficiency of the national airspace system.

Although some progress has been made in current research on remote tower controllers, there are still many unresolved key issues. Existing studies have not analyzed the factors affecting remote tower controllers' situational awareness comprehensively and deeply enough and lack a unified and effective assessment model. As a core factor affecting the safety and efficiency of air traffic control, the accuracy and validity of the assessment of situational awareness are crucial. Accurately assessing the situational awareness level of remote tower controllers is of non-negligible significance for optimizing the controller training system, improving the design of remote tower systems, and ensuring the safe and efficient operation of air traffic. However, there are differences in the existing research methods and indicator selection, which makes it difficult to compare and integrate the results of the studies and fails to provide strong support for practical applications. Therefore, this study is conducted to fill these research gaps, comprehensively and deeply explore the level of situational awareness of remote tower controllers, and construct a set of scientific and reasonable assessment index system and model, so as to provide theoretical basis and practical guidance for improving the safety and efficiency of air traffic management.

2. Materials and Methods

2.1. Experimental Apparatus

Collection of Heart Rate Variability Parameters: In this study, heart rate variability (HRV) parameters were collected using an Inner Balance device equipped with an ear sensor. This research apparatus includes a built-in ear sensor capable of capturing inter-

beat interval (IBI) parameters. The ear sensor can connect via Bluetooth, allowing HRV data to be transmitted to other mobile devices through an application. Additionally, the device is easy to install and suitable for dynamic testing, aligning with the experimental design requirements of this study. **Eye Movement Data Collection:** The Tobii Pro Eye Tracker was employed to analyze the eye movement behaviors of participants. This lightweight, head-mounted eye-tracking system minimizes restrictions on the subjects, ensuring that it does not interfere with their normal activities. The camera is mounted externally on the frame, positioned at the front of the forehead, and captures the controllers' field of view while tracking head movements. Under effective sampling conditions, the gaze position error is less than 0.5° . However, the collection of eye movement data may be affected for participants wearing corrective glasses. To address this issue, myopic controllers were provided with contact lenses to ensure accurate eye-tracking results. **Performance Assessment for Controllers:** In conjunction with the performance evaluation standards of the control unit, the author designed a Working Memory Assessment Scale for controllers. This scale primarily evaluates the controllers' working memory performance during remote tower operations, specifically focusing on the understanding phase of situational awareness formation. To ensure accuracy and real-time feedback, the scale was administered immediately after task completion.

Likewise, the author developed a Communication and Coordination Assessment Scale based on interviews with frontline controllers and related personnel. This scale assesses the controllers' abilities to process information and make decisions during the decision-making phase of situational awareness formation. To guarantee the accuracy and timeliness of the evaluation, this scale was also administered after task completion.

2.2. Experimental Procedure and Design

We selected the traditional control tower at JianDe General Aviation Airport and the remote tower at the Zhejiang Provincial Flight Service Center as the testing environments to ensure the reliability of the experimental results. We obtained the sample data from 10 controllers (8 men and 2 females) associated with the unit, whose ages ranged from 25 to 50 years.

We briefed each participant on the experimental protocols and equipment operating techniques prior to the evaluation to mitigate any extraneous variables that may influence the findings. Furthermore, we instructed participants to avoid strenuous activity prior to data collection and to ensure adequate rest and sleep. Figure 1 depicts the experimental setup.



Figure 1. Remote Tower Test Environment.

The experiment required all subjects to use the Tobii pro eye-tracker and the heart rate monitoring device under normal conditions for 30 min each. We conducted the trials in

real time, using a limited number of randomly placed aircraft to avoid disrupting the air traffic controllers at the general aviation airport during the tests. The measures sought to maintain a comparable workload for each controller, entailing the oversight of 2–3 aircraft in clear to partly cloudy weather circumstances.

In order to ensure the accuracy of the experimental results, factors that might affect the fatigue state of the controllers were strictly controlled. In terms of scheduling, the normal state experiment was scheduled between 8:00 a.m. and 11:00 a.m. This is because at the beginning of a workday, controllers are usually energetic and can be in a relatively stable non-fatigue state. The fatigue experiment was scheduled between 1:30 and 5:00 p.m. on the other day because, according to the pre-test survey, all participants had a habit of taking a nap, and conducting the experiment in the afternoon would make the participants more likely to be in a fatigued state.

Prior to the experiment, we standardized participants' daily activities. Participants were asked to maintain a normal work and life rhythm the day before the experiment, and to avoid overexertion or strenuous exercise. At the same time, we recorded the participants' sleep to ensure that they had enough sleep before the experiment. During the experiment, we provided participants with the same experimental environment, including consistent conditions of temperature, humidity, and light to minimize the influence of environmental factors on the fatigue state. In addition, we controlled the difficulty and duration of the experimental tasks to ensure that each participant performed the experiment under the same task load, so as to more accurately assess the effect of fatigue on situational awareness.

Furthermore, we categorized participants as experienced or trainee controllers based on their tenure. Mature controllers are those who hold a full controller's license issued by CAAC and have ≥ 5 years of frontline tower control experience. Trainee controllers are those who have completed the basic control training and passed the examination, but have less than 1 year of accumulated practical experience. The population distribution of controllers is shown in Table 1.

Table 1. Controller Population Distribution.

Clusters	N	Male (n)	Female (n)	Mean Age $\pm$ SD (Years)	Age Range (Years)
Mature controllers	5	4	1	34.2 $\pm$ 3.8	29–38
Trainee controller	5	4	1	25.6 $\pm$ 2.1	23–28

We terminated the recording of ocular movements and cardiac metrics after a total measurement duration of 30 min. Every 10 min, we documented the participants' performance and continued to observe pertinent facts related to their tasks. The supervisor evaluated the participants using the working memory assessment scale and the communication and coordination assessment scale. After the participants switched roles, the supervisor distributed subjective questionnaires and repeated the aforementioned data collection procedure with each participant.

The eye movement data were processed using Ergolab software v3.14 at the end of the trial, and outliers in the HRV data were corrected by Kubios HRV Premium software—Kubios HRV 2.2.

3. Data Analysis

Throughout this study, a significance level of $\alpha = 0.05$ was used for all statistical tests. This means that for any statistical analysis, if the p -value calculated is less than 0.05, the result is considered statistically significant. In other words, we reject the null hypothesis and conclude that there is a real effect or difference. Conversely, if the p -value is greater

than or equal to 0.05, we fail to reject the null hypothesis, suggesting that the observed effect may be due to random chance rather than a true underlying difference or relationship.

3.1. Analysis of SART Score Differences

The author conducted a paired-samples *t*-test on the SART scale scores measured by controllers in two different environments, remote tower (RETO) and conventional tower (COTO). The paired-samples *t*-test is effective in comparing the change in the mean of the same set of data under the two conditions of correlation and accurately examines the effect of environmental factors on the controllers' SART scale scores.

D (summed demand) denotes the extent to which the scenario demands attentional resources, S (summed supply) refers to the supply of attentional resources, and U (summed understanding) denotes the extent to which the subject understands the scenario.

After collecting and standardizing the data collected from the scale, the results of the normality test of the data showed that the *p* of the data in each group was greater than 0.05, obeying normal distribution and variance chi-square. Paired samples *t*-test can be used. Through the analysis, it was concluded that the controllers' degree of attentional demand D and the degree of situational comprehension U as well as the final situational awareness scores in the two experimental environments were significantly different ($p < 0.05$), and the degree of attentional resource supply S was not different ($p \geq 0.05$). As shown in Table 2.

Table 2. Results of paired-sample *t*-test analysis of SA scales.

Scale Indicators	Towers	Mean	SD	t	Sig
U	RETO	12.14	2.478	4.510	0.004
	COTO	9.286	1.603		
S	RETO	31.57	5.912	1.523	0.179
	COTO	27.429	3.047		
D	RETO	28	1.528	6.355	0.001
	COTO	23	2.160		
SA	RETO	48.286	5.499	2.719	0.035
	COTO	39.857	5.872		

The results of experiments indicate that as the control environment evolves, the attention demand placed on controllers in the remote tower is much greater than that in the conventional tower ($t = 4.510$, $\text{sig} = 0.004$). The attention demand level consists of three elements: situational instability, situational complexity, and situational variability. In the remote tower setting, controllers mostly interact with pilots via various electronic displays and communication devices, whereas conventional tower controllers depend on direct observation. The heightened concentration required in the remote tower, as opposed to the conventional tower, may arise from the distinct methods of information collecting, which may affect controllers' perception and comprehension of the situation. As a result, we identified significant disparities in attention demand levels.

The availability of attention resources, including mental arousal, attention allocation, attention focus, and residual energy, exhibited no significant variation ($t = 1.523$, $\text{sig} = 0.179$). This may be due to the need for controllers to maintain a uniform degree of vigilance in both settings to guarantee operational safety.

The volume of acquired information, the quality of that information, and the degree of familiarity with the context determine the comprehension of the situation. The disparities in the work environments of the Remote Tower and Conventional Tower, including visibility,

acoustics, and interference, may influence the controllers' perception and comprehension. The extent of visual scanning might result in fluctuations in cognitive load, thereby affecting the SART scores. Moreover, the displays in the Remote Tower provide extensive environmental data, facilitating a more natural information retrieval process. The remote tower may depend more on technological gadgets, which may vary in dependability and reaction time compared to the conventional tower. Consequently, controllers in the remote tower setting often obtain a bigger volume and caliber of information, along with enhanced situational awareness ($t = 6.355, p = 0.001$).

Furthermore, the disparities observed in the two situations are also influenced by psychological variables. Controllers may encounter diverse psychological conditions, such as stress and exhaustion, in various work environments, which might influence their situational awareness. The aforementioned elements may operate independently or synergistically, resulting in variations in the SART situational awareness ratings across controllers in remote tower and conventional tower settings ($t = 2.719, p = 0.035$).

As shown in Figure 2. Controllers demonstrate considerable variations across the two control contexts due to variances in the control environment, equipment, and psychological states. A lot of progress has been made in recent years in studying how people use classic tower controllers. However, subjective data representation can still show differences in how people perceive situations in two settings, but it is still open to biases and interference. Consequently, a comprehensive investigation of situational awareness among remote tower controllers is essential, highlighting the need for a thorough examination of diverse signs that might signify situational awareness inside the remote tower context.

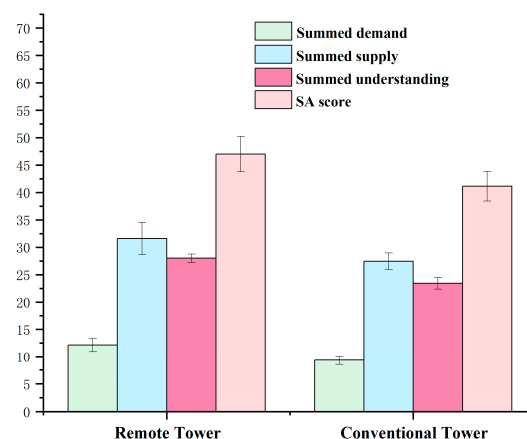


Figure 2. Comparison of Controller SART Scale Results at Traditional and Remote Towers.

3.2. Two-Factor ANOVA on Controller Situational Awareness Related Indicators

A two-way ANOVA was used in this section because we aimed to explore the effects of two independent variables (controller fatigue status and controller qualification) on multiple dependent variables (eye movement index, heart rate variability parameter, and self-contained scale scores, etc.) for the controllers in the remote tower condition. Two-factor ANOVA not only analyzes the main effect of each independent variable, but also examines the interaction effect between them, which is a more comprehensive and in-depth analytical method suitable for exploring the complex variable relationships in this study.

The fatigue state status of the experimentally measured within-subject factors was split into two levels (fatigue vs. non-fatigue). Each subject completed the control task in both states, and the task order was randomized in a Latin square design to control for order effects.

The trial was also divided into two levels (mature vs. trainee) for the between-subjects factor Flavor Controller Qualification. Dependent variables were seven eye movement

indices and heart rate variability parameters collected with a Tobii Pro eye-tracking device, as well as the self-developed Controller Working Memory Scale and the Communication Coordination Scale. Due to the gender imbalance (eight males and two females), gender was included as a covariate in a generalized linear model (GLM) to control for potential bias.

3.2.1. Analysis of Controllers' Eye Movement Characteristics

The eye movements of air traffic controllers are intricately associated with cognitive functions, since their behavior offers immediate insights into aviation traffic management. This research used a two-factor analysis, with the independent variables being the controllers' tiredness levels and their credentials. The dependent variables comprised seven eye movement metrics obtained via the Tobii Pro eye tracker: average blink count (ABC), fixation counts (FC), total fixation times (TFT), average fixation times (AFT), total saccade times (TST), average saccade count (ASC), and average pupil diameter (APD).

The mean of three repeated measurements of eye movement metrics for each subject in the same condition was taken to reduce random error. Normality of the indices was verified by the Shapiro–Wilk test (all $p > 0.05$). Therefore, we may employ a two-way ANOVA. The variance study primarily examined the impact of controller qualifications and tiredness levels on different eye movement characteristics. Specific values are shown in Table 3.

Table 3. Two-factor ANOVA for eye movement characteristics.

Norm	Condition	F	p
ABC	Fatigue state	18.830	0.00
	Controller qualifications	36.838	0.00
	Both Interaction	5.54	0.029
FC	Fatigue state	44.025	0.00
	Controller qualifications	0.381	0.544
	Both Interaction	0.253	0.620
TFT	Fatigue state	0.4896	0.00
	Controller qualifications	10.843	0.004
	Both Interaction	2.300	0.145
AFT	Fatigue state	19.856	0.00
	Controller qualifications	38.992	0.00
	Both Interaction	0.006	0.941
TST	Fatigue state	10.468	0.004
	Controller qualifications	1.649	0.241
	Both Interaction	0.657	0.427
ASC	Fatigue state	2.192	0.154
	Controller qualifications	0.906	0.353
	Both Interaction	4.690	0.043
APD	Fatigue state	142.717	0.00
	Controller qualifications	0.867	0.363
	Both Interaction	0.841	0.370

We conducted a two-way ANOVA on the ABC data, which revealed significant main effects for both tiredness state ($F = 18.830$, $p = 0.00$) and controller qualifications ($F = 36.838$, $p = 0.00$). We identified a significant interaction impact between the tiredness state and controller qualifications ($F = 5.541$, $p = 0.029$). The impact of the controller qualities on the ABC parameter was clearly visible.

The data revealed that while the tiredness levels of the remote tower controllers fluctuated, the average blink count markedly rose for both seasoned and novice controllers.

This indicates that tiredness affects eye movement patterns, possibly impairing situational awareness and overall effectiveness in air traffic control jobs.

We performed a two-way ANOVA on the fixation counts (FC) data, which showed a significant main impact of tiredness state ($F = 44.025, p = 0.00$), but the influence of controller qualifications ($F = 0.381, p = 0.544$) on the FC parameter was not significant. Furthermore, we observed no significant interaction between tiredness state and controller qualifications ($F = 0.253, p = 0.620$). The influence of the fatigue state on the FC parameter was significant. The findings demonstrate that both experienced and trainee air traffic controllers exhibited a declining trend in fixation points corresponding to variations in tiredness levels.

A two-way ANOVA on total fixation times (TFT) showed that tiredness state ($F = 4.896, p = 0.00$) and controller qualifications ($F = 10.843, p = 0.004$) had important main effects. We observed no significant interaction between fatigue state and controller qualifications for the TFT parameter ($F = 2.300, p = 0.145$). The impact of fatigue conditions on the TFT parameter was significant. The data indicate that when the tiredness levels of distant tower controllers varied, both seasoned and novice controllers showed a decline in fixation time.

For both tiredness state ($F = 19.856, p = 0.00$) and controller qualifications ($F = 38.992, p = 0.00$), a two-way ANOVA showed that there were significant main effects for average fixation times (AFT). The two factors did not significantly interact for AFT ($F = 0.006, p = 0.941$). The qualities of the controller have a considerable impact on AFT. The statistics illustrate that both experienced and trainee controllers exhibited a declining trend in average fixation time as their tiredness levels varied. A two-way ANOVA on total saccade times (TST) revealed a significant main effect for the tiredness state ($F = 10.468, p = 0.004$), although the impact of qualifications was not significant ($F = 1.649, p = 0.241$). The tiredness state and qualifications for TST did not significantly interact ($F = 0.657, p = 0.427$). The condition of weariness markedly affected the TST parameter. Data indicate that while the tiredness levels of distant tower controllers fluctuated, both seasoned and novice controllers exhibited a decline in saccade length. The examination of average saccade count (ASC) revealed that neither tiredness state ($F = 2.192, p = 0.154$) nor qualifications ($F = 0.906, p = 0.353$) significantly influenced the ASC parameter. We detected a significant interaction between tiredness state and controller qualifications ($F = 4.690, p = 0.043$). The interplay between fatigue levels and qualifications significantly influenced ASC parameters. The data indicate that while the tiredness levels of distant tower controllers varied, the average saccade counts of experienced controllers decreased, whereas those of trainee controllers escalated.

A two-way ANOVA revealed a significant main impact of the tiredness state on the average pupil diameter (APD) ($F = 142.717, p < 0.00$), although the influence of qualifications was not significant ($F = 0.867, p = 0.363$). We observed no significant interaction between tiredness state and qualifications for APD ($F = 0.841, p = 0.370$). The impact of controller qualifications on the APD parameter was significant. The data indicate that while the tiredness levels of distant tower controllers fluctuated, both seasoned and novice controllers had a diminishing trend in average pupil diameter. The study of each eye movement metric may be examined in conjunction with the aforementioned data and post-experimental interviews. Under typical circumstances, the frequency of blinking correlates with psychological states. Blink rates often increase under stressful situations and decrease while concentrating on a job. Figure 3a demonstrates that experienced controllers typically displayed greater blink counts than trainee controllers in both fatigued and non-fatigued conditions, possibly due to trainee controllers allocating more attention to their tasks, leading to a reduction in blinks relative to their experienced peers. Fixation points denote the spatial places that controllers concentrate on during a designated time period, with the quantity of fixation points correlating to the amount of information requiring processing.

The quantity of fixation points rises when controllers engage with regions of interest [30]. Figure 3b illustrates that experienced controllers exhibited marginally fewer fixation locations compared to trainee controllers. The superior experience of seasoned controllers, who may promptly concentrate on pertinent information upon receiving directives, may account for this gap, while trainee controllers may process information at a slower pace, leading to an increased number of fixation points.

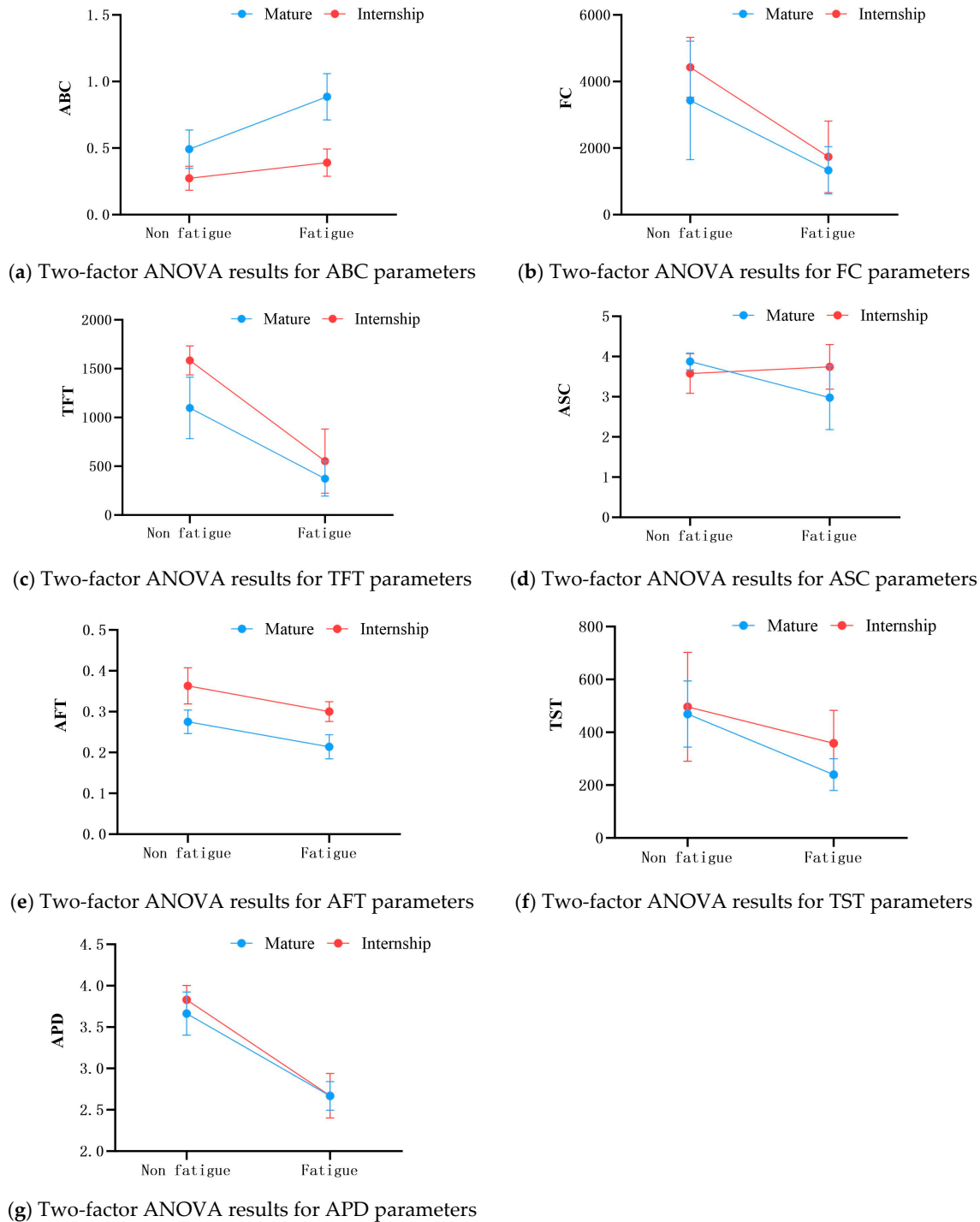


Figure 3. Comparison of two-factor ANOVA results for each eye movement parameter.

Experienced controllers, after acquiring flight information, often rely on memory to extract and verify details, using enhanced working memory in air traffic management and adopting a holistic view of airspace resources to maintain safe separations. Thus,

the total fixation length and average fixation time metrics for experienced controllers were much lower than those of trainee controllers in both exhausted and non-fatigued conditions, as seen in Figure 3c,d. The length of a saccade indicates the velocity at which controllers acquire information. Figure 3e shows a reduction in the saccade length for tired controllers compared to those in a non-fatigued state. Furthermore, seasoned controllers had somewhat reduced saccade durations compared to novice controllers, suggesting a decrease in information-acquisition velocity under fatigue. The reduction in information-gathering speed for seasoned controllers was less significant than that for novice controllers. Average saccade counts may reflect the concentration levels of controllers throughout the management process. Figure 3f demonstrates that experienced controllers exhibited lower average saccade counts in exhausted circumstances compared to non-fatigued situations, but trainee controllers displayed greater average counts in fatigued states, leading to contrasting patterns. This suggests that seasoned controllers maintain a more calm control state despite tiredness, resulting in diminished attention and reduced average saccade counts. Trainee controllers, with less situational awareness, may often alter their fixation locations to obtain more information, even when exhausted. Effective situational awareness is essential for controllers to manage emergencies correctly, underscoring the psychological maturity of seasoned controllers in contrast to trainee controllers, who may find it simpler to improve alertness.

The pupil is the tiny circular opening at the center of the iris, with its diameter principally regulated by the contraction and relaxation of the iris smooth muscle. The mean pupil diameter signifies the average size of a controller's pupils over time, showing the degree of stress encountered throughout the management process. Figure 3g illustrates a comparison of average pupil diameter measurements for controllers with differing qualifications across varied fatigue conditions. Both experienced and trainee controllers demonstrate a progressive reduction in average pupil diameter when fatigued. The decrease in pupil diameter indicates that tiredness results in lower tension levels, with trainee controllers exhibiting somewhat more stress than their experienced counterparts. In general, increased weariness is associated with reduced pupil diameters.

3.2.2. Analysis of Heart Rate Variability Parameters in Air Traffic Controllers

The psychological load significantly affects the incidence of human mistakes, since both extremely high and low psychological loads may result in the oversight of essential information [31]. This is especially important during the operation of remote tower controllers because safety depends on the controllers' ability to take appropriate actions. Mental stress triggers physiological changes in the heart and peripheral blood vessels. Stress influences heart rate, and heart rate variability (HRV) accurately measures the degree of alterations in cardiac rhythms. Heart Rate Variability (HRV) is an effective metric for evaluating the equilibrium between the sympathetic and parasympathetic nervous systems. Consequently, examining heart rate patterns may provide insights about personal psychological and physiological alterations, facilitating the evaluation of mental stress via HRV values [32]. This research used Kubios software (Kubios HRV 2.2) to examine the time-domain and frequency-domain characteristics of participants' heart rates, namely SDNN, NN50, LF, HF, and RMSSD. The specific values are shown in Table 4.

We performed a two-way ANOVA on the SDNN findings and found that neither the tiredness state ($F = 0.624$, $p = 0.439$) nor the controller qualifications ($F = 2.002$, $p = 0.172$) significantly influenced the SDNN parameter. Moreover, there was no notable interaction between the tiredness state and controller qualifications ($F = 0.00$, $p = 0.987$). The interplay between fatigue levels and controller qualifications significantly influenced the SDNN parameter. The SDNN index denotes the standard deviation of normal-to-normal

intervals and serves as a sensitive measure of sympathetic nerve activity. As mental stress increases, this indication often declines. Figure 4a illustrates that when the tiredness levels of distant tower controllers fluctuate, both seasoned and novice controllers show a declining trend in SDNN, with trainees seeing a somewhat lesser decline compared to their experienced counterparts.

Table 4. Two-factor ANOVA for HRV.

Norm	Condition	F	p
SDNN	Fatigue state	0.624	0.43
	Controller qualifications	2.002	0.172
	Both Interaction	0.00	0.987
NN50	Fatigue state	5.256	0.033
	Controller qualifications	0.661	0.426
	Both Interaction	0.100	0.755
LF	Fatigue state	0.017	0.899
	Controller qualifications	0.014	0.908
	Both Interaction	0.106	0.749
HF	Fatigue state	6.631	0.018
	Controller qualifications	0.613	0.443
	Both Interaction	0.318	0.579
RMDSS	Fatigue state	0.862	0.364
	Controller qualifications	0.137	0.715
	Both Interaction	2.630	0.121

A two-way ANOVA of the NN50 data revealed a significant main impact of the tiredness state ($F = 5.256$, $p = 0.033$), although the influence of controller qualifications ($F = 0.661$, $p = 0.426$) on the NN50 parameter was not significant. Furthermore, there was no notable interaction between the tiredness state and controller qualifications ($F = 0.100$, $p = 0.755$). The NN50 index denotes the proportion of consecutive R-R interval differences over 50 ms and serves as a sensitive measure for evaluating parasympathetic nerve activity. As mental stress rises, this measure often diminishes. Figure 4b shows that when the tiredness levels of distant tower controllers change, both experienced and trainee controllers show a decreasing trend in NN50. However, the decrease in NN50 for trainees is not as strong as it is for experienced controllers.

A two-way ANOVA for the LF findings indicated that neither tiredness state ($F = 0.017$, $p = 0.899$) nor controller qualifications ($F = 0.014$, $p = 0.908$) had a significant impact on the LF parameter. We observed no significant interaction between tiredness state and controller qualifications ($F = 0.106$, $p = 0.749$). The impact of controller qualifications on the LF parameter was significant. Most people use the LF index to assess brain function, as it indicates low-frequency sympathetic nervous system activity. This indication tends to rise with increasing mental stress. Figure 4c illustrates that when the tiredness levels of remote tower controllers fluctuate, both experienced and trainee controllers have a declining trend in LF, whereas trainee controllers exhibit an upward trend in LF data.

A two-way ANOVA on the HF data revealed a significant main impact of the tiredness state ($F = 6.631$, $p = 0.018$), although the influence of controller qualifications ($F = 0.613$, $p = 0.443$) on the HF parameter was not significant. We observed no significant interaction between tiredness state and controller qualifications ($F = 0.318$, $p = 0.579$). The condition of weariness significantly affected the HF parameter. Most people use the HF index, which indicates high-frequency sympathetic nervous system activity similar to LF, to assess brain function. As mental stress increases, this measure often declines. Figure 4d illustrates

that when the fatigue levels of remote tower controllers fluctuate, both seasoned and novice controllers exhibit an upward trend in HF, with novices displaying a little lesser rise compared to their experienced counterparts.

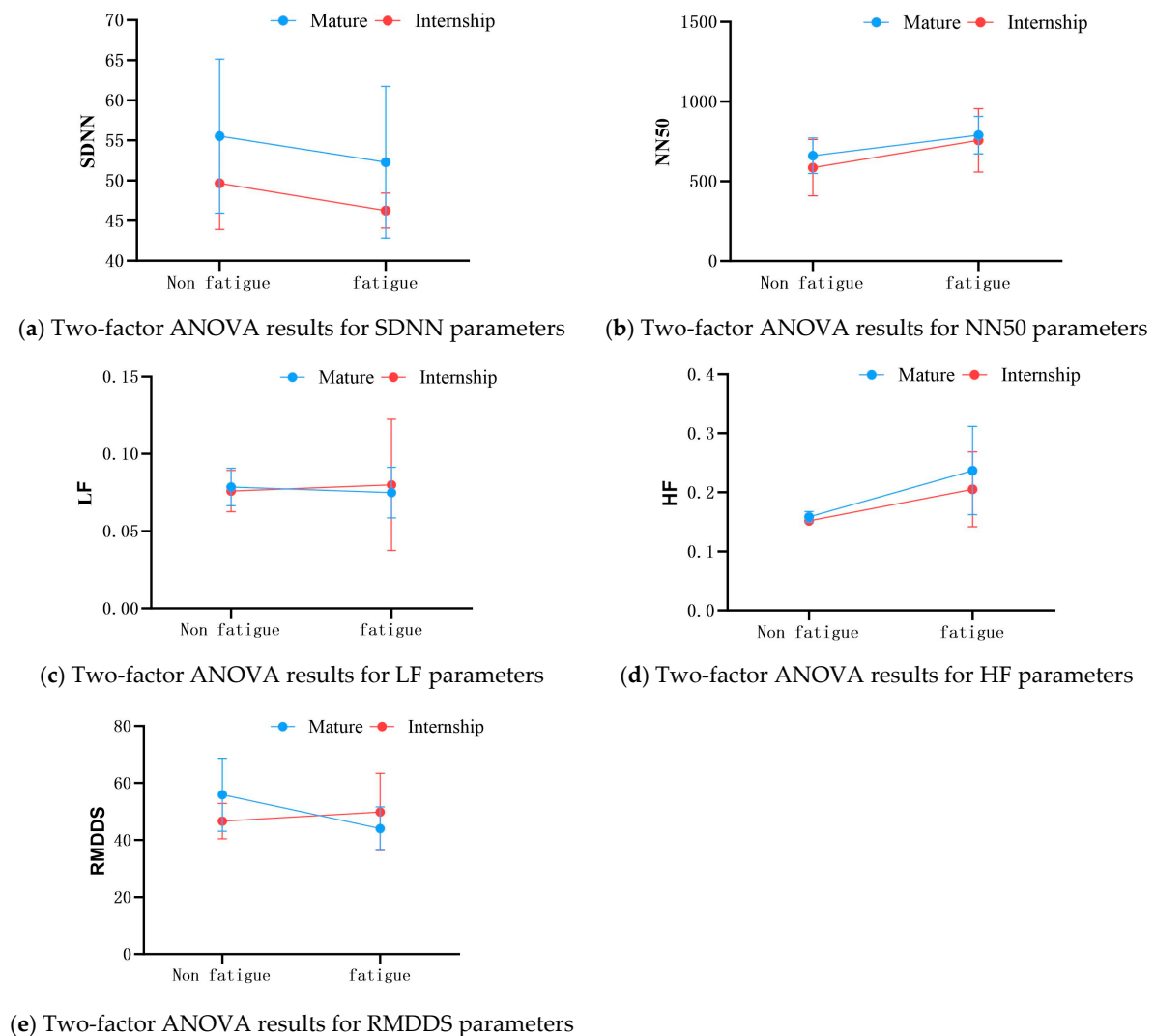


Figure 4. Comparison of two-factor ANOVA results for heart rate variability parameters.

The examination of heart rate variability metrics underscores the substantial influence of psychological stress on the physiological reactions of air traffic controllers. Comprehending the dynamics of HRV might facilitate the identification of possible stress-related problems that may result in human mistakes in air traffic control. Ongoing oversight and assistance in managing psychological stress may improve safety and performance in this high-pressure setting. Further research is required to explore therapies aimed at enhancing heart rate variability and mitigating the effects of psychological stress in controllers.

We performed a two-way ANOVA on the RMDDS results and found that neither the level of tiredness ($F = 0.862$, $p = 0.364$) nor the qualifications of the controllers ($F = 0.137$, $p = 0.715$) had a big effect on the RMDDS parameter. Furthermore, we observed no significant interaction between the tiredness state and controller qualifications ($F = 2.630$, $p = 0.121$). The interaction between controller fatigue and qualifications significantly influenced the RMDDS parameter. As a sensitive way to measure parasympathetic nerve activity, the RMDDS index finds the root mean square of the differences between two or more normal R-R intervals. As mental stress increases, this measure often declines. Figure 4e illustrates that while the tiredness condition of remote tower controllers fluctuated,

the RMDDS index for experienced controllers decreased, but the RMDDS index for trainee controllers had an upward trend.

3.2.3. Analysis of ATC Information Comprehension Ability

Understanding and recognition of the outside world pertain to humans' knowledge and evaluation of the essential components inside the perceptual memory process, along with the interconnections among those components [33]. The comprehension part entails integrating distinct perceptual information into a cohesive situational awareness via processes including recognition, analysis, and assessment. This component necessitates the amalgamation of knowledge to comprehend its influence on an individual's objectives and trajectory. The aviation safety report system indicates that pilots' failure to comprehend the situational context accounts for approximately 23.3% of incidents [34]. At this stage, the human brain does cognitive processing, integrating prior experiences and knowledge to understand the environment with the performance evaluation criteria of the control unit. The author developed a working memory assessment scale of 10 self-assessment tasks to evaluate controllers' working memory. This scale mainly assesses controllers' working memory performance in remote tower control operations based on their subjective experiences post-task execution, emphasizing their comprehension of information during the development of situational awareness.

When the data were checked for normality, all of the groups had p -values above 0.05, which means the data had a normal distribution, and two-way ANOVA could be used. The two-way ANOVA principally examined the impacts of controller credentials and tiredness levels on several eye movement characteristics. The findings demonstrated that both the tiredness state ($F = 125.3$, $p < 0.0001$) and controller qualifications ($F = 13.84$, $p = 0.0016$) had substantial major impacts. Moreover, there was no notable relationship between the tiredness state and qualifications about the information comprehension phase ($F = 2.264$, $p = 0.1497$). The controllers' weariness significantly affected their comprehension of information. Figure 5 demonstrates that while the tiredness levels of remote tower controllers fluctuated, both seasoned and novice controllers showed a decline in their working memory assessment scores. The deterioration of working memory and information comprehension was associated with the tiredness levels of controllers, with novice controllers exhibiting a more rapid drop than their seasoned counterparts.

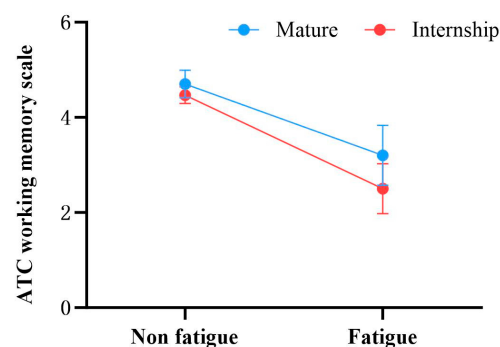


Figure 5. Comparison of Two Factor ANOVA Results of ATC Working Memory Scale.

3.2.4. ATC Information Processing and Decision-Making Analysis

The author conducted interviews with frontline controllers and pertinent individuals to evaluate their communication and coordination skills in remote tower operations. This resulted in the creation of an assessment scale for communication and coordination abilities tailored for remote tower controllers, which measures their information processing and decision-making phases during the construction of situational awareness.

On-duty supervisors used the scale throughout job execution to ensure the precision and promptness of the assessment, evaluating the remote controllers' performance in real time. The normality tests conducted on the data revealed that all groups exhibited p -values over 0.05, indicating a normal distribution and hence validating the use of a two-way ANOVA. This investigation mainly examined the impact of controller qualifications and tiredness levels on several eye movement characteristics. The results showed that the main effect on the information processing and decision-making phases was the controller's tiredness ($F = 98.97$, $p < 0.0001$), while the main effect on the phases of qualifications ($F = 2.489$, $p = 0.1342$) was not significant. Furthermore, there was no notable interaction between the tiredness state and qualifications for the information comprehension phase ($F = 0.09265$, $p = 0.7648$). The controllers' weariness significantly affected their information processing and decision-making capabilities.

Figure 6 illustrates that when the tiredness levels of remote tower controllers varied, both seasoned and novice controllers showed a decline in communication and coordination skills. The deterioration in the information processing and decision-making ability of controllers was associated with their degrees of weariness, with trainee controllers exhibiting lower average scores than their seasoned counterparts.

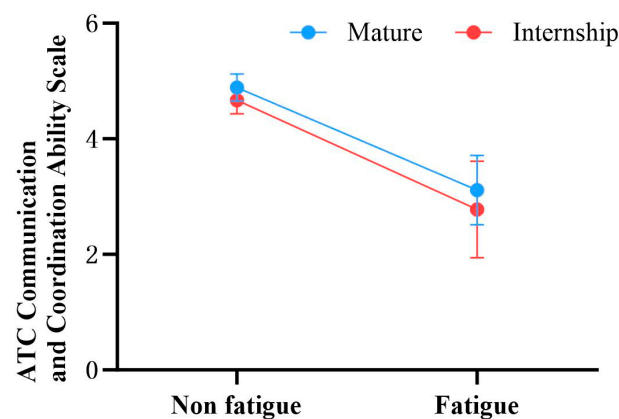


Figure 6. Comparison of Two Factor ANOVA Results of ATC Communication Coordination Scale.

4. EWM–TOPSIS–Gray Relational Degree Model

4.1. Assessment Index System for Situational Awareness Levels of Remote Tower Controllers

The individual abilities and experiences of controllers significantly impact their information processing, long-term memory, and operational effectiveness. Moreover, elements associated with the remote tower system—such as usability, interface design, transparency, work pressure and load, job complexity, and automation level—significantly influence the situational awareness of controllers. In this research, the author used eye movement metrics and heart rate variability metrics to illustrate the perceptual characteristics of controllers. Additionally, the author employed custom assessment scales for working memory and communication coordination to evaluate the controllers' comprehension of information during situational awareness development, as well as their ability to process information and make decisions based on their performance in remote tower operations.

Using the above-mentioned analytical framework, we can carefully look at the basic processes that help distant tower controllers become more aware of their surroundings through the lenses of perception, comprehension, and decision making. This research enables the identification of the primary elements impacting the situational awareness of remote tower controllers.

The methodology for evaluating the situational awareness level of remote tower controllers comprises one primary evaluation indicator, three secondary assessment indicators, and 19 tertiary assessment indicators, as shown in Table 5 below.

Table 5. Indicator system for assessing the level of situational awareness of remote tower controllers.

Secondary Indicator	Indicator Code	Tertiary Indicators
Perceptual Ability	A1	Average Fixation Duration
	A2	Average Pupil Diameter
	A3	NN50
	A4	HF (High Frequency)
	A5	Fixation Duration
	A6	Average Blink Frequency (Inverse)
	A7	Saccade Duration (Inverse)
	A8	Number of Fixation Points (Inverse)
	A9	Average Saccade Frequency
Information Understanding Ability	B1	Information Reception and Filtering
	B2	Information Integration And Association
	B3	Information Storage and Retrieval
	B4	Information Interpretation and Judgment
	B5	Information Updating and Adaptation
Information Processing and Decision-Making Ability	C1	Information Acquisition Efficiency
	C2	Information Analysis Quality
	C3	Timeliness of Decision Making
	C4	Communication and Coordination
	C5	Average Fixation Duration

The data were derived from the experimental measurements described in the previous section. Specifically, the eye movement index data were collected from 10 controllers using a Tobii Pro eye-tracking device under different experimental conditions; the heart rate variability index data were collected from the Inner Balance device; and the data for the Working Memory Assessment Scale and the Communication Coordination Assessment Scale were based on the subjective self-assessment of the controllers after completing the tasks and real-time assessment by the shift supervisors. These data were organized and pre-processed as input data for the combined model to assess the controllers' situational awareness level.

4.2. Determining Indicator Weights Using the Entropy Method

Entropy weight method (EWM) is an objective assignment method, and its core idea is to determine the weight of each indicator based on the information entropy of the data. The information entropy reflects the degree of disorder of the data, and the smaller the entropy value, the greater the amount of information contained in the indicator, which should be given a higher weight in the comprehensive evaluation. The specific calculation steps are as follows:

The original data are first standardized, followed by the calculation of each indicator's entropy and entropy weight. The detailed steps are as follows:

(1) Construct a Normalized Decision Matrix Utilize the standardized sample data to create a normalized decision matrix comprising 24 evaluation objects and 19 evaluation indicators $Y = (y_{ij})_{24 \times 19}$.

(2) Calculate the Entropy of Each Evaluation Indicator Initially, compute the entropy values for each evaluation indicator. e_j , Then, calculate the entropy weight for each indicator based on the entropy values w_j , where $1 - e_j$, represents the coefficient of variation for the j -th indicator:

$$e_j = -\frac{1}{\ln(24)} \sum_{i=1}^{24} \frac{y_{ij}}{\sum_{i=1}^{24} y_{ij}} \ln \frac{y_{ij}}{\sum_{i=1}^{24} y_{ij}} \quad (1)$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{19} (1 - e_j)} \quad (2)$$

4.3. TOPSIS–Gray Relational Mode

The TOPSIS method is a ranking selection method that approximates the ideal solution, and it has been widely used in the comprehensive evaluation of indicators in some fields of study. The relative advantages and disadvantages of each program are determined by calculating the distance of each program from the positive ideal solution and the negative ideal solution. The positive ideal solution is the combination of the optimal value of each indicator, and the negative ideal solution is the combination of the worst value of each indicator. However, the single TOPSIS method has certain application defects, for this reason, the text adopts the EWM–TOPSIS–Gray correlation analysis method to comprehensively evaluate the level of situational awareness of the controllers under the condition of having remote towers and obtains the weights of each index through the entropy value method and integrates the basic idea of gray correlation analysis method on the basis of TOPSIS method. Based on the basic idea of TOPSIS method, the Euclidean distance and correlation degree between each scenario and the ideal scenario are considered, so as to measure the advantages and disadvantages of the scenarios in a comprehensive way [35]. The fundamental calculating stages are as follows:

(1) Construct the weighted normalized matrix. Multiply the normalized matrix Y by the weight vector w_j to obtain the weighted normalized matrix Z :

$$Z = (z_{ij})_{24 \times 19} = (w_j y_{ij})_{24 \times 19} \quad (3)$$

(2) Determine the positive and negative ideal solution sequences for each indicator:

$$Z^+ = \left\{ \max_{1 \leq i \leq 24} Z_{ij} \right\} = [z_1^+, z_2^+, \dots, z_{19}^+] \quad (4)$$

$$Z^- = \left\{ \min_{1 \leq i \leq 24} Z_{ij} \right\} = [z_1^-, z_2^-, \dots, z_{19}^-] \quad (5)$$

(3) Calculate the Euclidean distances of each indicator representing situational awareness level to the positive D_i^+ and negative ideal solution sequences D_i^- :

$$D_i^\pm = \sqrt{\sum_{j=1}^n (z_{ij} - z_j^\pm)^2} \quad (6)$$

(4) Using the weighted normalized matrix Z , calculate the gray correlation coefficients of the i th evaluation scheme with respect to the corresponding indicators of the positive and negative ideal solutions:

$$\zeta_{ij}^\pm = \frac{\min_i \min_j |z_j^\pm - z_{ij}| + \rho \max_i \max_j |z_j^\pm - z_{ij}|}{|z_j^\pm - z_{ij}| + \rho \max_i \max_j |z_j^\pm - z_{ij}|} \quad (7)$$

In the equations $i = 1, 2, \dots, 24$; $j = 1, 2, \dots, 19$, ρ corresponds to the indicators, and the distinguishing function, ρ , is typically set to 0.5 based on previous research [36].

Subsequently, the gray correlation degrees between each indicator parameter and the positive and negative ideal solutions are calculated, denoted as R_i^+ and R_i^- :

$$R_i^\pm = \frac{1}{n} \sum_{j=1}^n \xi_{ij}^\pm \quad (8)$$

(5) The Euclidean distances and gray correlation degrees from all evaluations are then subjected to a non-dimensionalization process:

$$\beta_i = \frac{\theta_i}{\max_{1 \leq i \leq 24} (\theta_i)} \quad (9)$$

In the equations, let θ_i represent the Euclidean distances, D_i^+ , D_i^- , and of each evaluated sample to the ideal solution, as well as the gray correlation degrees, R_i^+ and R_i^- . β_i denotes the non-dimensionalized Euclidean distances and gray correlation degrees, which are represented as G_i^+ , G_i^- and S_i^+ , S_i^- , respectively. A larger value of D_i^- and R_i^+ indicates that the scheme is closer to the ideal solution, whereas an increase in D_i^+ and R_i^- signifies that the scheme is farther from the ideal solution. By considering the non-dimensionalized Euclidean distances and gray correlation degrees, the comprehensive proximity of each scheme can be calculated as follows:

$$f_i^+ = \frac{G_i^- + S_i^+}{2} \quad (10)$$

$$f_i^- = \frac{G_i^+ + S_i^-}{2} \quad (11)$$

$$\mu_i = \frac{f_i^+}{f_i^+ + f_i^-} \quad (12)$$

f_i^+ comprehensively reflects the proximity of each treatment to the ideal solution, while f_i^- indicates the degree to which each treatment deviates from the ideal solution. μ_i represents the comprehensive proximity degree. The treatments are ranked according to the size of μ_i ; a larger comprehensive proximity degree indicates a superior treatment, whereas a smaller degree indicates a less favorable treatment.

4.4. Comprehensive Evaluation and Analysis of the Level of Situational Awareness

The two-way ANOVA indicates that under remote tower settings, varying qualifications and tiredness levels of air traffic controllers lead to substantial differences in the parameters of each indicator. We thoroughly investigate and assess the situational awareness levels of air traffic controllers in remote tower settings using an entropy–TOPSIS–Gray relational degree model. We have selected nineteen assessment indicators and processed the experimental data using the aforementioned processes. Initially, we determine the weights of each indicator using the entropy approach, as shown in Table 6:

Subsequently, the TOPSIS method is employed to calculate the Euclidean distances D_i^+ and D_i^- , while the Gray relational analysis method is utilized to compute the Gray relational degrees R_i^+ and R_i^- . Finally, the comprehensive proximity degree, μ_i , for each treatment scheme is derived by integrating D_i^+ , D_i^- , R_i^+ , and R_i^- . The results are presented in Table 7.

Table 6. Entropy value method to find the weight of each indicator.

Indicator	Entropy	Coefficient of Variation	Weight
A1	0.9412	0.0588	0.0653
A2	0.9128	0.0872	0.0969
A3	0.9541	0.0459	0.0509
A4	0.9546	0.0454	0.0504
A5	0.9203	0.0797	0.0885
A6	0.9493	0.0507	0.0563
A7	0.9442	0.0558	0.0620
A8	0.9621	0.0379	0.0421
A9	0.9630	0.0370	0.0411
B1	0.9784	0.0216	0.0240
B2	0.9522	0.0478	0.0531
B3	0.9560	0.0440	0.0489
B4	0.9755	0.0245	0.0272
B5	0.9757	0.0243	0.0270
C1	0.9755	0.0245	0.0272
C2	0.9566	0.0434	0.0482
C3	0.9609	0.0391	0.0434
C4	0.9521	0.0479	0.0532
C5	0.9625	0.0375	0.0416

Table 7. Comprehensive evaluation of the results of the analysis.

No	Euclidean Distance		Gray Relational Degree		Coupling		μ_i	R
	D_i^+	D_i^-	R_i^+	R_i^-	f_i^+	f_i^-		
001	0.0373	0.0509	0.7307	0.6871	0.4204	0.7540	0.3580	11
002	0.0331	0.0584	0.7953	0.6435	0.4815	0.6913	0.4106	4
003	0.0346	0.0538	0.7515	0.6663	0.4437	0.7182	0.3819	10
004	0.0379	0.0584	0.7501	0.7006	0.4801	0.7681	0.3846	9
005	0.0324	0.0591	0.7714	0.6641	0.4860	0.6992	0.4100	5
006	0.0369	0.0550	0.8349	0.6176	0.4559	0.7058	0.3924	8
007	0.0390	0.0479	0.7730	0.6390	0.3982	0.7366	0.3509	12
008	0.0263	0.0636	0.8305	0.6134	0.5230	0.6155	0.4594	1
009	0.0281	0.0604	0.8099	0.6230	0.4978	0.6370	0.4387	2
010	0.0318	0.0589	0.8035	0.6334	0.4857	0.6738	0.4189	3
011	0.0315	0.0556	0.7790	0.6407	0.4590	0.6765	0.4042	6
012	0.0349	0.0555	0.7889	0.6404	0.4581	0.7040	0.3942	7
013	0.0571	0.0344	0.6976	0.7313	0.2895	0.9460	0.2343	22
014	0.0574	0.0392	0.7335	0.7210	0.3290	0.9411	0.2590	19
015	0.0532	0.0380	0.7317	0.6904	0.3190	0.8872	0.2645	18
016	0.0506	0.0461	0.7646	0.6738	0.3837	0.8551	0.3098	15
017	0.0580	0.0312	0.6724	0.7530	0.2641	0.9668	0.2145	24
018	0.0552	0.0337	0.7063	0.7140	0.2845	0.9190	0.2364	20
019	0.0472	0.0433	0.7280	0.6905	0.3604	0.8376	0.3008	16
020	0.0608	0.0335	0.6845	0.7674	0.2822	1.0000	0.2201	23
021	0.0581	0.0350	0.7030	0.7309	0.2947	0.9535	0.2361	21
022	0.0456	0.0446	0.7546	0.6668	0.3713	0.8094	0.3145	14
023	0.0504	0.0397	0.7221	0.7053	0.3320	0.8741	0.2753	17
024	0.0450	0.0447	0.7632	0.6575	0.3724	0.7978	0.3183	13

The total proximity degree represents the situational awareness levels of air traffic controllers in distant tower settings. Table 4 shows that a higher proximity degree correlates with an enhanced level of situational awareness for each controller, as determined by their comprehensive proximity degrees.

Figure 7 displays the ranking of the indicators, derived from the weights determined in Equation (2). The top five indications are average blink frequency, length of eye saccades, average fixation duration, fixation time, and average pupil diameter. Figure 8 depicts the complete scores for the assessment items as per Equation (12). Evaluation items 1 to 12 denote data gathered from air traffic controllers during non-fatigue intervals, and evaluation objects 13 to 24 pertain to data acquired during fatigue intervals. The data unequivocally demonstrates that the situational awareness of air traffic controllers operating under remote tower settings is much superior during non-fatigue intervals in contrast to fatigue intervals.

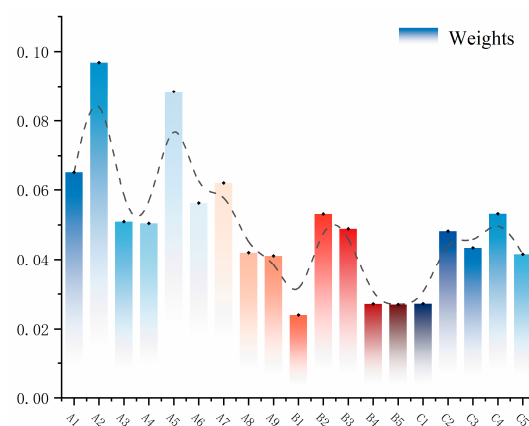


Figure 7. Comparison Bar Chart of Indicator Weight.

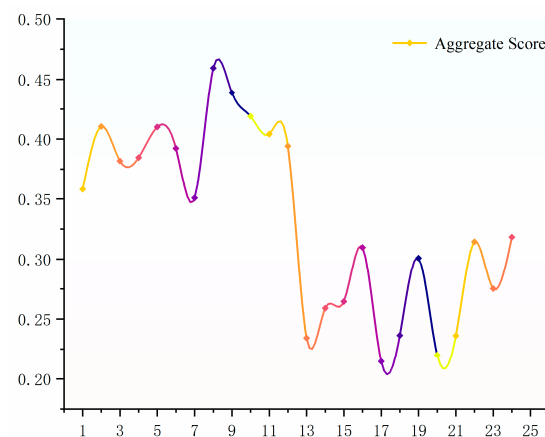


Figure 8. Overall scoring situation of evaluation objects.

5. Discussion

Focusing on the assessment of situational awareness levels of remote tower controllers, this study achieved a series of valuable research results, as well as certain limitations that point the way for subsequent research.

In terms of research results, this study found significant differences between controllers' situational awareness scale scores in remote and traditional tower environments, with the differences in the level of attention demand and situational comprehension being particularly prominent. This is consistent with the findings of Peter Kearney et al. who noted significant differences between remote tower and traditional physical tower

operations in terms of controllers' psychological demands, time demands, level of effort, and level of frustration. In the remote tower environment, controllers rely primarily on electronic screens and communication devices for information, a method of information acquisition that is very different from that of direct observation in traditional towers, resulting in a significant increase in their attentional demands. At the same time, differences in the reliability and responsiveness of technical equipment and systems in remote towers compared to traditional towers affect the controllers' understanding of the scenarios, which in turn leads to significant differences in the level of scenario understanding.

Quantitative analysis of the perception, comprehension, and decision making related levels for remote tower controllers showed that several metrics had significant variations in controller qualifications, fatigue status, and their interactions. For example, among the eye movement indicators, the average number of blinks and gaze duration were significantly affected by controller qualification and fatigue state. This is consistent with the idea that eye movement behavior can reflect cognitive activities in related studies. Mature controllers and trainee controllers had different trends in eye movement indicators when facing fatigue, reflecting their differences in information processing ability and psychological state. Mature controllers are experienced and can still maintain a relatively stable control state under fatigue, but their attention will be reduced, whereas trainee controllers, although their situational awareness is relatively weak, will acquire more information by frequently shifting their gaze point when fatigued, showing a stronger ability to raise their vigilance.

In terms of HRV parameters, some indicators such as NN50 and HF are significantly affected by fatigue, which provides a basis for evaluating the psychological and physiological changes in controllers through HRV parameters. However, the use of HRV parameters to study fatigue or situational awareness has been controversial, and the results of the present study help to further explore this issue, but more research is needed to verify its reliability.

By constructing the EWM-TOPSIS-Gray correlation model, this study identified the sensitivity indicators affecting the situational awareness of remote tower controllers, in which the average number of blinks and the duration of eye jumps were weighted higher. This result provides an important reference for the assessment of situational awareness, indicating that these indicators should be emphasized when assessing the level of controllers' situational awareness.

Compared with other studies, this study is innovative in its methodology and indicator selection. The combination of subjective and objective data and the comprehensive use of multiple indicators to assess situational awareness make up for the previous shortcomings of relying only on subjective measurements. However, the current research on situational awareness of remote tower controllers is still in the developmental stage, and there are differences between different studies in terms of indicator selection, research methodology, and research subjects, which makes it difficult to compare the results of the studies, and more standardized studies are needed in the future to enhance the comparability of the results.

This study also has some limitations. In terms of sample selection, only 10 controllers from Jiande Tonghang Airport were selected as the sample in this study, which is a small sample size and relatively single source, and may not fully reflect the real situation of controllers in different regions and experience levels. In addition, the gender imbalance (eight men and two women) may have some impact on the results of the study, and although gender is included as a covariate in the model, it is still difficult to completely eliminate its potential impact. In terms of the experimental environment, although real traditional and remote tower environments were selected, the experimental process may be interfered by a variety of factors, such as the uncertainty of the flight volume of the navigable airports and

the limitation of the experimental time, which may affect the accuracy and reliability of the data.

Based on the above limitations, future research can be conducted in several directions. First, expand the sample size and increase the diversity of the sample to cover controllers from different regions, genders, and experience levels in order to improve the generalizability of the study results. Second, further optimize the experimental design to control more interfering factors, such as more strictly controlling the amount of flights and weather conditions during the experiment to ensure the accuracy of the experimental data. In terms of indicator selection, more indicators related to situational awareness can be explored, and emerging technologies, such as virtual reality and brain–computer interface, can be combined to obtain more comprehensive and accurate physiological and psychological data, so as to study the situational awareness of controllers in depth. In addition, longitudinal studies can be conducted to track the changes in situational awareness of controllers at different stages to provide more targeted recommendations for training and management.

In summary, this study provides a valuable reference for assessing the situational awareness level of remote tower controllers, but it still needs to be improved and expanded in subsequent studies to better meet the actual needs of air traffic management.

The present study had some limitations in terms of sample selection, with only 10 participants (8 males and 2 females) included. The main reason for the small sample size is that this study focuses on the specific occupational group of remote air traffic control tower controllers, which is relatively concentrated in distribution and has a special nature of work, which requires a high level of time and energy to participate in the experiment. When contacting relevant units and personnel to participate in the experiment, there are greater difficulties in coordinating the time and work schedule of all parties.

Nonetheless, this study is still significant. The preliminary results of the experiment provide a key direction for subsequent research. By studying these 10 participants, we have successfully verified some of the research hypotheses and identified some key indicators related to situational awareness. In the follow-up, we plan to conduct further studies to increase the sample size in order to enhance the reliability and generalizability of the findings.

6. Conclusions

The results of this study reveal the status of situational awareness levels of air traffic controllers in different control situations. The results showed significant differences in situational awareness scores between controllers working in remote and traditional tower environments, particularly in attention and situational awareness tasks.

Next, levels of perception, comprehension, and decision making relevant to tower controllers were assessed. Combining subjective and objective data, the study found that controllers' situational awareness levels varied significantly by qualification as well as by fatigue level. The study of eye movements, heart rate, and two subjective indicators revealed that experienced controllers demonstrated better mental safety skills, while novice controllers were more inclined to increase their alertness in comparison.

In this study, key indicators affecting the situational awareness of remote tower controllers were identified and a comprehensive assessment model was constructed using the entropy weighting–TOPSIS–gray correlation analysis framework. The model identified the five most important metrics: average blink frequency, eye hop length, average gaze duration, gaze time, and average pupil diameter. A modified gray correlation TOPSIS methodology yields a composite proximity score that reflects the controller's overall level of situational awareness. This model clarifies the composition, performance, and importance of situational awareness in the work of remote tower controllers and accurately describes

the related operational processes and influencing factors. This paradigm helps controllers to better understand the psychological and physiological processes involved and to identify the factors affecting their situational awareness.

Author Contributions: In the conceptualization phase, T.L. and M.H. jointly played a leading role, proposing the core ideas and framework for the research, laying the theoretical foundation for the entire study. M.H. was responsible for designing specific research methods, carefully selecting and using appropriate software tools to conduct the research, and taking on the main tasks of data collection, organization, and analysis, including rigorous formal analysis and in-depth research to ensure data accuracy and completeness. During the process of writing the paper, T.L. and M.H. devoted themselves to crafting the initial draft, meticulously refining both the content organization and language expression. They then repeatedly reviewed and edited the paper to continuously improve its quality. Additionally, M.H. was responsible for presenting the research findings in a visual format, making the complex research content easier to understand and showcase. Z.Z. participated in the validation of the research results, cross-checking and verifying the research data and conclusions from different perspectives, providing important assurance for the reliability of the study. All authors actively participated in various stages of the research process and reached a unanimous agreement on the final published manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Key project of the Civil Aviation Joint Fund of the National Natural Science Foundation of China, grant number U2233209.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Chen, L. Discussion on civil aviation air traffic control informatization construction in the new period. *Times Financ.* **2017**, *35*, 276+279.
2. Zhang, J.; Xiang, Y.; Zhang, P.; Wang, Q. Enlightenment of European remote tower operation concept and technical requirements to China. *Aeronaut. Comput. Technol.* **2018**, *48*, 122–126.
3. Zhu, H.; Yang, S. SESAR Launches 15 Large-scale Air Traffic Management Demonstration Projects. *Command. Inf. Syst. Technol.* **2014**, *5*, 90.
4. Josefsson, B.; Polishchuk, T.; Polishchuk, V.; Schmidt, C. Scheduling air traffic controllers at the remote tower center. In Proceedings of the 2017 IEEE/AIAA 36th Digital Avionics Systems Conference (DASC), St. Petersburg, FL, USA, 17–21 September 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–10.
5. EASA. *Notice of Proposed Amendment 2017–21, Technical and Operational Requirements for Remote Tower Operations*; EASA: Cologne, Germany, 2017.
6. SESAR Joint Undertaking. *SESAR Solutions Catalogue*, 2nd ed.; SJU: Luxembourg, 2017.
7. Hollan, J.; Hutchins, E.; Kirsh, D. Distributed cognition: Toward a new foundation for human-computer interaction research. *ACM Trans. Comput.-Hum. Interact. (TOCHI)* **2000**, *7*, 174–196. [[CrossRef](#)]
8. Kearney, P.; Li, W.C.; Zhang, J.; Braithwaite, G.; Wang, L. Human performance assessment of a single air traffic controller conducting multiple remote tower operations. *Hum. Factors Ergon. Manuf. Serv. Ind.* **2020**, *30*, 114–123. [[CrossRef](#)]
9. Lu, T.T.; An, Z.; Shen, H.; Wang, Y.; Li, W.C. Comparative Analysis of Remote Tower Controllers and Traditional Physical Tower Controllers Based on Human Ergonomics in China. In Proceedings of the International Conference on Human-Computer Interaction, Washington, DC, USA, 29 June–4 July 2024; Springer Nature: Cham, Switzerland, 2024; pp. 259–268.
10. Huang, T.; Zhang, C. A review of remote tower operation assessment research. *Aeronaut. Sci. Technol.* **2022**, *33*, 1–10. [[CrossRef](#)]
11. Wang, D. Research on Visual Search Mode in Radar Control. Master's Thesis, Civil Aviation University of China, Tianjin, China, 2016.
12. Blaylock, B.K. Risk perception: Evidence of an interactive process. *J. Bus. Res.* **1985**, *13*, 207–221. [[CrossRef](#)]

13. SESAR Joint Undertaking. *Operational Services and Environment Description (OSED) for Remote Provision of ATS to Aerodromes: DEL06. 09. 03*; SESAR Joint Undertaking; Bruxelles, Belgium, 2015.
14. Beier, K.; Gemperlein, H. Simulation of infrared detection range at fog conditions for Enhanced Vision Systems in civil aviation. *Aerosp. Sci. Technol.* **2004**, *8*, 63–71. [[CrossRef](#)]
15. Endsley, M.R. Toward a Theory of Situation Awareness in Dynamic Systems. *Hum. Factors J. Hum. Factors Ergon. Soc.* **1995**, *37*, 32–64. [[CrossRef](#)]
16. Lundblad, K.; Speziali, J.; Woltjer, R.; Lundberg, J. FRAM as a risk assessment method for nuclear fuel transportation. In *Proceedings of the 4th International Conference Working on Safety, Crete, Greece, 30 September–3 October 2008; Volume 1*, p. 223-1.
17. Hartman, B.O.; Secrist, G.E. Situational awareness is more than exceptional vision. *Aviat. Space Environ. Med.* **1991**, *62*, 1084–1089.
18. de Carvalho, P.V.R. The use of Functional Resonance Analysis Method (FRAM) in a mid-air collision to understand some characteristics of the air traffic management system resilience. *Reliab. Eng. Syst. Saf.* **2011**, *96*, 1269–1275. [[CrossRef](#)]
19. Van De Merwe, K.; Van Dijk, H.; Zon, R. Eye movements as an indicator of situation awareness in a flight simulator experiment. *Int. J. Aviat. Psychol.* **2012**, *22*, 78–95. [[CrossRef](#)]
20. Fidopiastis, C.M.; Drexler, J.; Barber, D.; Cosenzo, K.; Barnes, M.; Chen, J.Y.; Nicholson, D. Impact of automation and task load on unmanned system operator's eye movement patterns. In *Foundations of Augmented Cognition. Neuroergonomics and Operational Neuroscience: 5th International Conference, FAC 2009 Held as Part of HCI International 2009 San Diego, CA, USA, July 19–24, 2009 Proceedings 5*; Springer: Berlin/Heidelberg, Germany, 2009; pp. 229–238.
21. Liang, N.; Yang, J.; Yu, D.; Prakah-Asante, K.O.; Curry, R.; Blommer, M.; Swaminathan, R.; Pitts, B.J. Using eye-tracking to investigate the effects of pre-takeover visual engagement on situation awareness during automated driving. *Accid. Anal. Prev.* **2021**, *157*, 106143. [[CrossRef](#)] [[PubMed](#)]
22. Lafond, D.; Champagne, J.; Hervet, G.; Gagnon, J.F.; Tremblay, S.; Rousseau, R. Decision Analysis Using Policy Capturing and Process Tracing Techniques in a Simulated Naval Air-Defense Task. *Proc. Hum. Factors Ergon. Soc. Annu. Meet.* **2009**, *53*, 1220–1224. [[CrossRef](#)]
23. Li, W.C.; Kearney, P.; Braithwaite, G.; Lin, J.J. How much is too much on monitoring tasks? Visual scan patterns of single air traffic controller performing multiple remote tower operations. *Int. J. Ind. Ergon.* **2018**, *67*, 135–144. [[CrossRef](#)]
24. B-TM-2017-01; Reference Learning Materials for Fatigue Management of Civil Aviation Controllers. Civil Aviation Administration of China: Beijing, China, 2017.
25. Endsley, M.R.; Garland, D.J. *Situation Awareness Analysis and Measurement*; Erlbaum: Mahwah, NJ, USA, 2000.
26. Yang, Y.; Ma, B.; Cheng, L. Cognitive load evaluation method in multi-factor flight conflict detection. *J. Beijing Univ. Aeronaut. Astronaut.* **2024**, *11*. [[CrossRef](#)]
27. Li, Y.H. Heart rate variability analysis of plateau highway drivers. *Compr. Transp.* **2019**, *41*, 7882.
28. Sun, H.; Jin, X.; Xie, F.; Sun, X.; Zheng, S. Effects of long-term working memory and attention allocation on situational awareness of crew members of armored vehicles. *Acta Armamentarii* **2022**, *43*, 2749–2760.
29. Yuan, W. Experimental Study on Dynamic Visual Characteristics of Automobile Drivers in Urban Road Environment. Ph.D. Thesis, Chang'an University, Xi'an, China, 2008.
30. Guo, Y.; Fu, R.; Zhang, J.; Yuan, W. Distribution law of automobile driver's gaze point under different channel width conditions. *J. Traffic Transp. Eng.* **2006**, *6*, 51–54.
31. Durantin, G.; Gagnon, J.F.; Tremblay, S.; Dehais, F. Using near infrared spectroscopy and heart rate variability to detect mental overload. *Behav. Brain Res.* **2014**, *259*, 16–23. [[CrossRef](#)]
32. Castaldo, R.; Montesinos, L.; Melillo, P.; James, C.; Pecchia, L. Ultra-short term HRV features as surrogates of short term HRV: A case study on mental stress detection in real life. *BMC Med. Inform. Decis. Mak.* **2019**, *19*, 1–13. [[CrossRef](#)] [[PubMed](#)]
33. Zhang, M.; Wang, H.; Fu, Q. Human Factors Analysis of Aeronautical Maintenance Based on Functional Resonance Method. *Chin. J. Ergon.* **2018**, *2*, 69–73.
34. TOFTGARD. *Visualisering av FRAM*; University of Linköping: Linköping, Sweden, 2010.
35. Liu, X.B.; Xu, C.K.; Li, L.X. Evaluation model of aviation material suppliers based on entropy—TOPSIS—Grey correlation degree. *J. Ordnance Eng. Coll.* **2017**, *29*, 7–10.
36. Li, X.; Wang, J.; Tang, C. Demand-side responsiveness prediction based on grey and Markov system theory. *Electr. Power Demand-Side Manag.* **2020**, *22*, 71–76.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.