https://doi.org/10.1016/j.aei.2021.101325

A human-centred approach based on functional near-infrared spectroscopy for adaptive decision-making in the air traffic control environment: A case study

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Acknowledgement

The authors would like to express their gratitude and appreciation for the anonymous reviewers, the editor-in-chief and the guest editors for providing valuable comments for the continuing improvement of this article. The research is supported by *School of Mechanical Engineering, Shandong University, Jinan, China*, *Research Committee and Interdisciplinary Division of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University, Hong Kong SAR, China (RH1W) and School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore.* The research is also supported by *grant from the MOE (Ministry of Education in China) Project of Humanities and Social Sciences (grant number 17YJC760009), Shandong Social Science Planning*

Fund Program (grant number 18CCXJ23), and the Interdisciplinary Division of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University, HKSAR (Grant number: ZVS9).

Declarations of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Abbreviation

ATC, Air traffic control; ATM, Air traffic management; ATCOs, Air traffic controller; HFs, Human factors; DM, Decision-making; IA, Intelligent automation; EEG, Electroencephalography; fNIRS, Functional near-infrared spectroscopy; fMRI, Functional magnetic resonance imaging; GSR, Galvanic skin response; VAS, Visual analogue scoring; RPFC, right prefrontal cortex; LRFC, left prefrontal cortex; RMC, light motor cortex; LMC, left motor cortex; ROL, right occipital lobe; LOL, left occipital lobe.

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Abstract

Safety-critical systems like air traffic control (ATC) are usually less automated than might be expected by the public, so human intelligence will remain at the core in the decision-making (DM) process. Meanwhile, human factors (HFs) need to be fully considered in the DM process, which can design the ATC system to be more intelligent and more adaptive to the behaviour of the user. However, the existing DM research lacks the systematic methods that fully consider human performance in a smart manner. This study proposed a human-centred adaptive DM methodology that combines subjective and objective measurements made by functional near-infrared spectroscopy (fNIRS) via intelligent automation (IA). Moreover, this paper also described a case study of radar display map operation, including descriptive and optimised maps, to illustrate the proposed approach and verify its feasibility and effectiveness. The results were determined by jointly considering the user-generated and system-generated data and suggested that the proposed approach could capture subjective and objective data, take into consideration the HFs information to provide real-time online feedback and adjust the decision support system to HFs. It is hoped that this study can promote the methodology of human-centred subjective and objective data-driven applications in the future ATC environment adaptive decision research.

Keywords: Air traffic control; Adaptive decision-making; Functional Near-Infrared spectroscopy; Human factors; Intelligent automation

1. Introduction

With the gradual development of technology and artificial intelligence, many robust and adaptive decision-making (DM) methods are being explored for developing real-life applications of engineering, such as transport systems, smart city, and inventory management, thereby increasing the convenience and reducing the risk inherent in engineering applications [1-3]. According to the latest annual global statistics reported by the International Civil Aviation Organization, the number of airline passengers is expected to reach 10 billion by 2040 [4]. Air traffic control (ATC) is responsible for resolving operational conflicts on the approach route and ensure passenger safety, as well as air traffic management (ATM) in the terminal manoeuvring area [5, 6]. The role of air traffic controllers (ATCOs) which involves continuous acquisition of the latest flight status and coordinates from several sources to make ATM decisions is becoming more significant [7, 8]. Normally, the work pressure of ATCOs increases with the volume of air traffic in the terminal manoeuvring area, leading to potential dangers. Hence, it is necessary to develop an advanced DM approach that can adapt to the mental condition of the ATCOs and control ATC system automatic parameters to ensure the efficiency and safety of air traffic operations [9, 10].

Making ATC decisions is deemed as a typical multi-criteria DM problem [5, 6, 11, 12]. Following the common approach in operations research and optimisation methods, the aircraft conflicts under the condition of uncertainty can be resolved by adjusting the speed, angle, and accelerations of the aircraft [13-16]. Yet the ATC operating system should not perform automatic adjustment based only on numerical data. Feyer et al. [17] showed that 90% of accidents at workplaces are caused principally by human error. Human factors (HFs) play a crucial role in improving system performance, reducing operating errors and enhancing occupation safety in the workplace. The greater the cognitive workload on the operators, the more likely it is that fatigue will occur and increase the possibility of erroneous work decisions being made. In the ATC field, zero tolerance for errors is mandatory because ATCOs' work has a direct implication regarding passenger safety. Therefore, HFs such as ATCOs' mental status should be taken into consideration. However, in spite of most DM methods involving human performance research currently, they only rely on the analysis of accumulated human experience and behaviour [18-20]. Such methods are likely to be seriously affected by the mentality of the decision maker and will not perform real-time feedback in response to environmental changes.

Therefore, the present circumstances lead to the unilateral (system-oriented or human-oriented) design outputs of the ATC operating system, which often result in a disconnection in DM between humans and the system. To maintain an appropriate operation level for the human-machine system and avoid placing the working state of ATCOs in underload or overload, HFs must be more considered in the DM process reasonably by introducing intelligent automation (IA) into the ATC workplace in the future.

The recent developments in neuroscience have made it possible to apply neuroimaging technology to detect the emotional and cognitive states of subjects and merge their data with other decision support systems. Neurophysiological measures, including Electroencephalography (EEG), functional Near-Infrared Spectroscopy (fNIRS), functional Magnetic Resonance Imaging (fMRI), and other bio-signals, such as Electrocardiography and Galvanic Skin Response (GSR) are used for human performance assessment [21]. Electrocardiography and GSR activities merely highlight certain mental states (stress, mental fatigue, drowsiness), while fMRI requires extremely exacting operating conditions [21]. EEG data are affected by various physiological noise signals. Besides, attachment to the body requires scalp abrasion and the application of a conductive gel. These necessities place restrictions on the subjects, which are not conducive to their executing tasks. Therefore, fNIRS, which does not have these disadvantages, is preferable for assessing human physiological performance in operational environments.

Safety-critical systems like ATC are usually less automated than might be expected by the public [22]. Human intelligence will remain at the core of the DM process. Although the current studies on advanced DM technologies and DM methods report a great improvement in the ATC field [23], there are still several challenges in their application and the related human activities: 1) Mainstream DM methods mainly take an aircraft's numerical data into consideration. However, the internal state of ATCOs cannot be detected and HFs do not receive consideration when manipulating and making decisions on operations, which has led to a failure to realise human-centred automatic regulation of ATC. 2) Most human performance and HFs assessment and detection methods are not efficient enough to provide both subjective and objective data in real time to support the DM process and elements in design, development, and optimisation of ATC system behaviour.

To address the above challenges, this research proposed an integrated DM method that combines subjective, behavioural, and neurophysiological measurement into ATC. The results from this study will contribute to a better understanding of human performance (ATCOs' workload, interaction, and mental status) in real time and thereby provide appropriate countermeasures (e.g. external automation will take over some of ATCOs' tasks when ATCOs are in a poor state) for the specific user-centred automatic regulation of ATC. Meanwhile, this process will add significant value in the provision of a useful approach and framework concerning data acquisition and analysis to assess machine and user state in real time of the entire ATC system. Moreover, by collecting and processing the subjective and objective data (e.g. user-created and system-generated data), the effectiveness and application of HFs can be evaluated based on data being driven to guide the development and optimisation of ATC system design. Operational insights from the findings would be useful in the development of ATCOs' training, cognitive identification, system decision behaviour, and human-machine interaction design.

The rest of the paper is organised as follows: Section 2 introduces some preliminaries of the proposed method. Section 3 illustrates the overall framework of DM in the ATC. Section 4 presents a case study using the radar map display interface to make the proposed decision research framework more specific and verify the effectiveness of the proposed method. Section 5 discusses and analyses the research results. Sections 6 sets out the managerial implications of this research. Section 7 states the contributions to the current literature in this field and the future direction of research that it suggests.

2. Related studies

Three streams of literature are relevant to this research, namely DM, HFs and cognitive fatigue measurements in ATC. The related literature is reviewed in this section to find the gaps in the research and build research strategies specific to the ATC system upon review of the theoretical foundations of the above aspects.

2.1. DM studies

The ATC system plays an important role in ensuring the flight efficiency and safety of aircraft by maintaining a safe longitudinal or vertical distance between aircraft and by changing the speed and deviating aircraft from hazardous areas to eliminate (or reduce) conflicts between aircraft on flight routes and other emergencies. The ATCOs need to monitor radar displays at all times to ensure the safety of various flights and their path movements along paths at different speeds and altitudes. In the last 20 years, the cause of approximately 70% of aircraft accidents was found to be ATCOs operating errors [24]. Creating advanced systems to support the DM process in ATC in order to reduce the error in DM by ATCOs, increasing the convenience of human-machine systems, and ensuring the stability and safety of ATC have always been important research directions [25].

The research on DM in the ATC system mainly includes expert systems, dynamic programming, path planning techniques, resilience engineering and metaheuristics [26, 27]. Cafieri et al. [13] proposed aircraft mixed-integer nonlinear programming modelling, based on speed regulation by acceleration or deceleration, to avoid aircraft conflicts while keeping their trajectories unchanged. Evans et al. [14] systematically collected the opinions of airlines through methods such as averaging, voting, and ranking, and then applied the game-theoretic approach and Monte Carlo methods to test the potential of airline strategic behaviour. The meta-heuristic framework based on variable neighbourhood search was proposed by Alonso-Ayuso et al. [28], which can be used to deal with conflict detection and resolution of such problems relating to aircraft by adjusting the angle of the aircraft. Moreover, the application of artificial intelligence to support the DM process in the ATC field has also attracted researchers' attention. Multi-agent-based modelling is frequently adopted in collaborative and complex DM processes by representing the entities of control centres, airports, lanes, etc. Agogino et al. [29] presented a multi-agent algorithm, where agents use reinforcement learning to reduce congestion through local actions. Each agent as a waypoint is responsible for three functions, ensuring separation between aircraft, ordering delays on the ground and changing the routes of aircraft. Lovato et al. [27] proposed a control strategy based on decisions on the longitudinal speed of flights without changing the route. Two series of fuzzy models based on Mamdani structure were adopted to quantify the level of longitudinal conflict between aircraft and to order aircraft to accelerate by a certain extent, thereby reducing or eliminating the possibility of conflict. However, Parasuraman et al. [22] have shown that a safety-critical system is usually a human-machine collaborative system. Most of the safety-related decisions are made by humans, and computer systems are used as auxiliary tools to assist controllers in their monitoring and communication tasks. Although the above systems make a certain contribution to the development of DM, these systems do not gather reliable information to understand the internal state of ATCOs to support IA progress in the ATC field.

To meet the ATC system's IA during the DM process, it is necessary to estimate and predict the status indicators of ATCOs through some scientific methods. Task execution, [18] such as the explicit measurement of errors committed while executing a task, the number of control actions, the efficiency of communications and time, decision and action frequency, as well as empirical research, including instantaneous self-assessment [30], NASA task load index [31], and the subjective workload assessment techniques [32] can measure the quality of cognitive decisions to some degree. Xiaotian et al. [33] confirmed the mental landscape of ATCOs through the locus of attention scale, and the results suggested that subjects with a high overall degree of thinking are more sensitive to potential conflict events, which provided a reference for ATCOs' selection and training. Wee et al. [34] attempted to synchronise the dynamic changes in humans and the system to monitor the operational behaviour and mental status of the whole system using a real-time eye tracking system. Dumais et al. [35] used a real-time eye tracking system to identify different user types by capturing information such as the gaze time of the eyes and the corresponding heat map to better design a search interface and adjust the system behaviour. Borst et al. [36] studied the control performance and operant behaviour of ATCOs during a transfer manipulation in different target scenarios through two-day behaviour analysis and discussed the short-term effects of ecological interface design.

Although the subjective and behavioural methods contribute to refining the level assessment of the user's status, the contribution is limited to the user's awareness, subjective perception, and the length of interval between the occurrence of an event and its assessment by the subject. With the rapid development of physiological measurement technology, it has been widely demonstrated that neurophysiological measurements of discriminating cognitive demand fluctuations transcend both behavioural and subjective measures [37]. The online neurophysiological measurements are not only used as support tools in operative activities but also as monitoring techniques [38], enabling the measurement of any changes in cognitive activity immediately, which can help the system manipulate the task demands and make adjustments to achieve the optimal level of work. Di Flumeri et al. [4] presented a vigilance and attention controller, which integrated the EEG and eye-tracking techniques.

The purpose was to evaluate the level of vigilance of ATCOs and to adjust the level of automation of the interface itself while working with highly automated human-machine interfaces. In the product scheme evaluation field, Lou et al. [39] utilized cloud models and EEG to form an integrated DM method, obtain the internal experience of design experts and target users, and provide professional test data to improve product design and development. The adoption of physiological and neurological tools to help understand the state of human perception while using engineering systems is more common in HFs research [40]. To improve upon the maximum efficiency of the existing ATC system, it is urgent to adopt convenient, scientific and effective methods to provide reliable feedback on the internal state of ATCOs and to reveal the current adaptive DM and IA level of the human-machine system.

2.2. Human factors studies

The purpose of studying HFs is to simultaneously consider human capabilities, defects and needs, so that products can be adapted to suit human characteristics. That is, HFs play an important role in the ATC system, which determines whether ATCOs can work comfortably and then adjust the operating level of the system to ensure ATCOs' efficiency. HFs have always been a major area of research in aviation [41]. The United States and Europe are paying more attention to HFs in the ATC system by gaining a better understanding and integration of HFs performance in the pursuit of superior business performance and security.

Human-machine interfaces, radar maps, voice interaction and radio communication help ATCOs to have a landscape of the latest traffic situation for ATM. Many high-frequency problems encountered in ATC operation are caused by unreasonable design [42]. Therefore, the research on interface and system designs of the ATC system has increased gradually. In order to solve the problem of coarse-grained rotation interaction of ATC automation operation, Luciani et al. [43] developed a set of low-fidelity prototypes by using auxiliary sketch models to perform fine-grained interaction on the radar display human-machine interface and re-designed the display and interaction formats of the interface elements in the system. Van Paassen et al. [44] presented a shared representation of 4D trajectory management design based on the cognitive systems engineering framework, and also adopted a formative approach in the field of analysis of 4D trajectory planning. Ten Brink et al. [45] introduced a conceptual interface for air traffic flow-based perturbation management in ATC. Their proposed system can enable ATCOs to manipulate multiple flows of traffic by facilitating interaction with a path-planning algorithm to change the route of several aircraft along an airway.

What calls for special attention is that individual factors, including the changes in workload, fatigue, stress and situational awareness, are important predictors for ATCOs when making decisions. All of these factors caused by the machine and environmental factors generally affect people's intervention and understanding of the system. By understanding the impact of these factors on the performance of ATCOs, specific solutions can be proposed. Trapsilawati et al. [46] measured HFs in conflict resolution, enduring mental workload, trust, dependence, and situation awareness under four conditions. Lyu et al. [47] introduced an HFACS-BN model (HFACS: Human factors analysis and classification system; BN: Bayesian network) to combine the subjective information of experts and objective data of accident reports, to evaluate training, physical fatigue, and mental state. The top five most influencing factors of HFs affecting the ATC system can also be obtained with the measurement proposed by Lyu et al. [47], that is, training, physical fatigue, mental state, ineffective monitoring, and ATC software/hardware.

In spite of some progress having been made on HFs research in the ATC field, most are considered and adjusted unilaterally (by the system or human intervention) or without a reasonable method to assess the HFs application, especially in effect on individual factors. Progress has not gone far enough towards realising human-machine fusion, nor have researchers evaluated the verification scheme further to optimise its design. In the current state, there is a major gap in the system, because it is unable to obtain physiological unconscious objective data through effective means to support the adjustment of the system to the user’s state and optimise system behaviour, thereby strengthening the human-machine connection.

Effective integration of HFs could cover the design of all the system elements, such as tools, human-machine interface, procedures, roles and communication flows [48]. The research design of the system elements extends from detailed basic design elements (lights and ergonomic design and colours) to high-level aspects that affect the DM process (assessing the cumulative workload or fatigue induced in the operator by a new sector configuration). Compared to other safety-critical and high-hazard domains, ATC is characterised by the key role played by HFs. Different HFs incorporated into the system will affect the cognitive load of ATCOs determining whether the decision is correct. The results of the evaluation of HFs performance affect the implementation and presentation of the design of elements ranging from system interface to workflow procedures and may necessitate re-design of the system. Evaluation of HFs' performance is an effective way to significantly improve the stability of the system and reduce errors. Furthermore, it is also a common method of decision processing, and to some extent, it is the basis of realising the maximum potential of an IA system.

2.3. Cognitive fatigue measurement studies

The safety of the system depends on the attention and cognitive level of the operators in the operating environment, such as aviation, railway, maritime and road transport. The industries are now seeking more automated systems and assistive technologies in their daily operation. This should be the long-term focus in traffic monitoring because reliance on human monitoring of the system may lead to degradation of vigilance and a potential increase in the number of errors, which may lead to failure of the system [7, 49]. Human error will lead to serious and dramatic consequences [38]. Cognitive fatigue is closely related to the improvement or deterioration of the users' performance [50]. The quality of the HFs assessed by the ATC system will directly determine the level of cognition in the ATCOs' operation as affected by boredom, drowsiness or closer vigilance. Therefore, in ergonomics and HFs research, it is crucial to have a reliable estimation of the actual cognitive workload experienced by the operators and design a user interface that can preserve a proper level of the user's mental workload, avoiding either an under or overloaded state [51]. This is also an important component of the system's adaptive DM, which lays the foundation for the adjustment and improvement of human-machine design.

Cognitive workload refers to the dynamic relationship among the cognitive resources that are needed to carry out a task [52]. The interactive behaviour of the ATC system based on human cognitive laws is of great significance, so it is possible to reduce the rate of manual error by adjusting the cognitive load of ATCOs. Neurophysiological techniques can assess the cognitive status of humans with a high degree of reliability, even in operational environments [53, 54] and also transcend both behavioural and subjective measures in discriminating cognitive demand fluctuations [38]. Dehais et al. [55] developed an fNIRS-EEG-based passive brain-computer interface system to monitor changes in pilots' cognitive fatigue in flight missions (flight simulation and real flight) and the results showed that more information was missed in the second phase than in the first phase; meanwhile, it also demonstrated that fNIRS and EEG-based systems can monitor psychological states in a working environment and noisy environment. Di Flumeri et al. [56] simulated a real driving experiment, inferring the driver's psychological and cognitive load based on the driver's brain activity through EEG. Zhao et al. [57] used EEG to measure the mental load and cognitive fatigue level of drivers in 90 minutes of continuous driving in order to find more reliable physiological measurements for driving mental fatigue. In order to measure the real state of cognitive change, Dehais et al. [58] under the condition of a real flight, used a 32-channel dry EEG system to measure the pilot's psychological fatigue and overload, and the results showed that the occurrence of mental fatigue is associated with higher theta and alpha band power, which provides the feasibility of evidence for detecting neural cognitive fatigue and load research. Li et al. [59] used the fNIRS to detect and compare cerebral cortical activity in two stroke rehabilitation models, in order to reveal the multisensory mechanism. Bu et al. [60] revealed the physiological mechanism of patients with mild cognitive impairment through effective connectivity by fNIRS. Liu et al. [61] used the fNIRS system to record the changes in a driver's actual driving activity and analysed the effective relationship between the brain network and cognitive load while driving.

As mentioned in the introduction, fNIRS is more suitable than EEG for this study. It is safe, portable, user-friendly and relatively inexpensive, with rapid application times and near-zero run-time costs. So it could be a potential portable system for measuring cognitive workload in realistic settings. Despite the advances in automation technology, neurophysiological measurement will play a central role in the study and application of ATCOs' job knowledge in the work environment [48]. Adaptive systems driven by ATCOs' psychological cognition state have become an important research direction [62]. It is essential to integrate human performance into the ATC system to increase its resilience and tolerance to errors [48]. Therefore, combining the objective (fNIRS technology) and subjective (experience and behaviour) measurement would appear more suitable in realistic environments for recognising the nature of spontaneous brain activity and other inner activity to improve and modulate the interaction between the operator and the system itself.

2.4. Research gaps

As introduced in Section 2.1, 2.2, and 2.3, the internal state of ATCOs and the human-machine fusion, especially subjective and objective research methods that provide reliable feedback, have not been fully considered in the advanced DM process of the ATC system. This may be due to most operating processes performing automatic adjustment only using numerical data and ignoring the role of operators, which might be difficult to evaluate through the existing quantitative methods, resulting in inaccurate data and failing to realise the human-system connection closely and reasonably. Meanwhile, there is little information to study a user-centred and data-driven framework for advanced DM of the ATC system. To address the above issues, the human-centred adaptive DM method that combines subjective and objective measurements made by fNIRS via intelligent automation is desirable.

3. The overall framework of data-driven DM on ATC

ATCOs should be at the centre of the entire process of IA and adaptive DM process in the ATC system. The proposed method considers the application and impact of HFs on the system and the subjective behaviour and neurophysiological changes that the ATCOs show. **Figure 1** illustrates the overall framework of the research method, which is divided into three parts: platform layer, data layer and application layer. The platform layer is in charge of providing research materials and elements (e.g. user and machine) to meet the conditions of data input. The data layer, based on subjective and objective data (e.g. brain science data) [63], mainly processes data acquisition, storage, analysis, and transmission. The application layer can provide the guidance for system adjustment and design elements (e.g. automatic level or performance design) in light of the above data results representing both physical and psychological implication and signal, and then serve to system parameters.

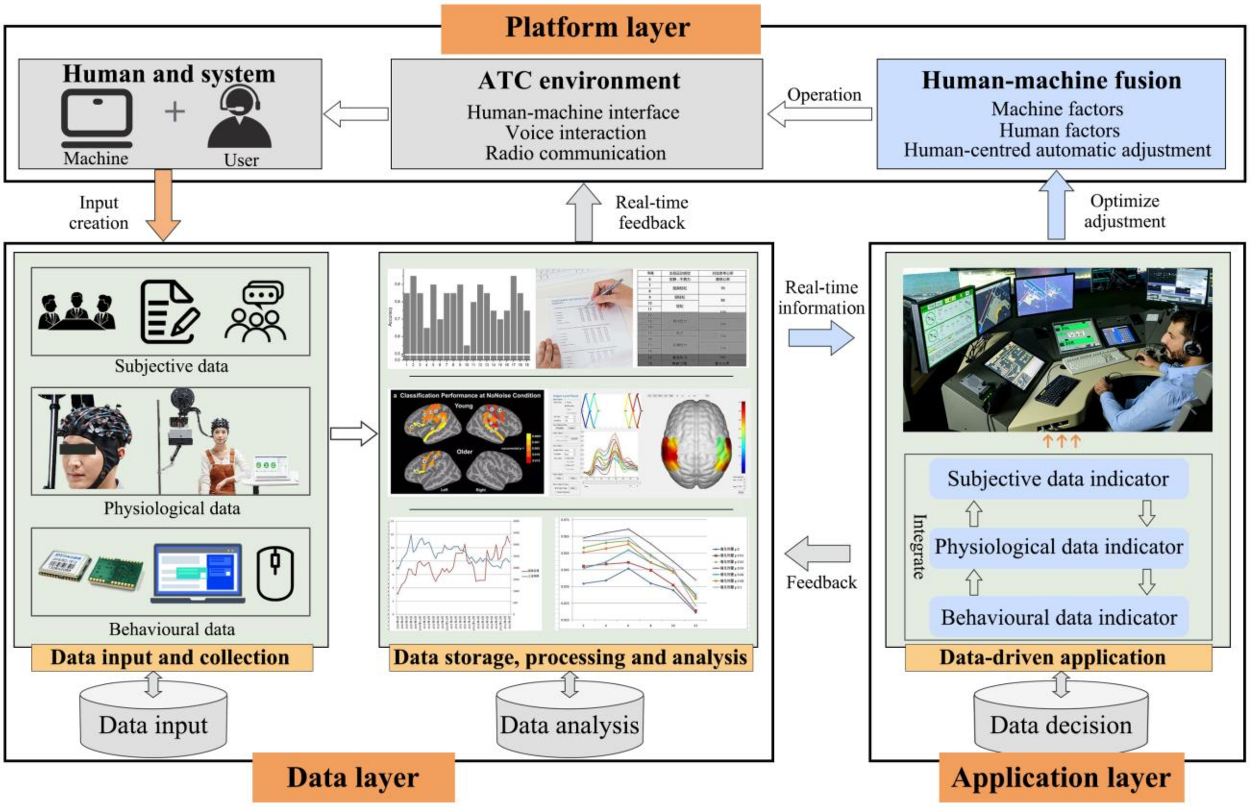

Figure 1. Overall framework of the data-driven DM process

3.1. Platform layer of the framework

The platform layer mainly includes the existing ATC system elements (i.e. hardware and software, as well as human and machine), such as human-machine interface, voice interaction, radar map, radio communication and so on, which provides the experimental conditions and materials for the data-driven research. Meanwhile, this layer also involves design and optimisation progress based on reliable data and parameters to prompt the ATC system to become smarter and friendlier for ATCOs, guaranteeing the high-efficiency operation with advanced DM. For example, Luciani et al. [43] re-designed the display and interaction formats of the interface elements in the system by using auxiliary sketch models based on users' preference and experience.

3.2. Data layer of the framework

3.2.1. Data input

The data layer includes data input and data analysis. Data input is mainly involved in the data collection function of the whole DM process. All the decisions that are supported by subjective or objective data which have certain defects. To ensure the orderly operation of the ATC system, the first step in its design framework is the collection of subjective, behavioural and physiological data to help reduce one-sidedness in the process and ensure that the system's adaptive DM moves in the correct direction. Both ATCOs and machine are regarded as the research objects. Subjective data in the form of quantitative and qualitative subjective information was collected from the ATCOs through the use of questionnaires, interviews and discussions and included visual analogue scoring (VAS), fatigue severity scale, NASA-Task Load Index questionnaire and a focus group. Physiological data collection was based on the real-time monitoring of ATCOs' neuronal activity in the fNIRS system during operational interaction and real-time recording of the user's unconscious feedback data, such as oxygenated haemoglobin concentration, cerebral cortex activation level and functional connectivity between brain regions, etc., to collect the objective information of ATCOs in the current state. The acquired behavioural data, such as operation reaction time, correct rate, situational awareness, and user operation flow through computer, sensor, mouse, and keyboard input, shows the behavioural status in the course of performing tasks, and is non-participatory observation. The specific implementation methods that the ATCOs use to increase the efficiency of their performance for doing specific experimental tasks may be noted for inclusion in the operating procedures.

3.2.2. Data analysis

The main work of the data analysis included data storage and transformation, data processing and data analysis and transmission. Firstly, subjective and objective data, such as changes in oxygenated haemoglobin concentration, rating scales, accuracy, and reaction time were recorded and stored in an unstructured fashion and subsequently arranged in an appropriately structured relational database system [64]. Not only structured query language was used to manage unstructured data that may appear in this article (mainly subjective and behavioural). Before storing semi-structured data, a simple conversion step was required to facilitate subsequent analysis. For example, the qualitative information or semantic words on the subjective scale and behaviour data were converted into a score scale through a Likert scale or the attention point scale. After data storage and transformation, data cropping, data denoising, data filtering and data conversion were required to improve the data's quality by noise filtering to ensure the effectiveness and reliability of data analysis. Next, the processed data were analysed to show the implied information with simple and clear results to clarify the relationship between the data results and the system application. For example, a generalised linear model was used to analyse the time series data of neuroimaging fMRI and fNIRS technology to obtain the degree of influence of the corresponding stimulation on the activation of the cerebral cortex [59]. The results of subjective, behavioural and physiological data were then normalised.

3.3. Application layer of the framework

The analysed data could then be used in the implementation of some data-driven application services based on results signals via data characteristics recognition, such as the adjustment of human-machine interface, the optimisation of radar maps, and the fine-tuning of voice-interactive and system automation level changes to meet the needs in its current state. Meanwhile, understanding the role of the HFs in the ATC system is necessary for achieving the ideal state of human-machine integration and decision processing in the ATC system. The evaluation system based on the subjective and objective score of the system design scheme can be used to further support and improve the ATC system design, as shown in **Figure 2**.

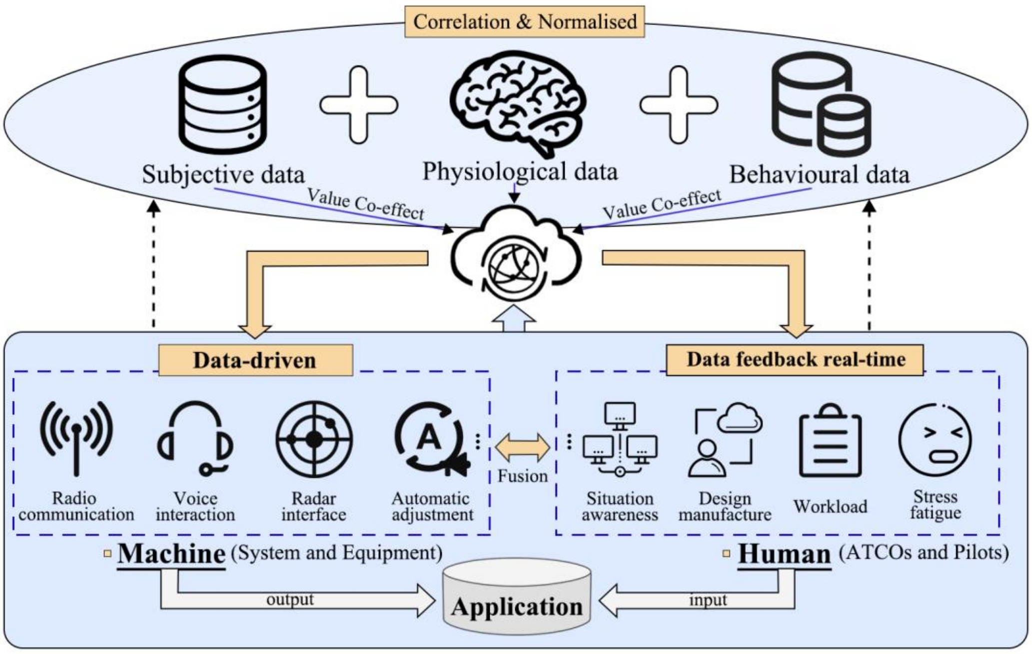

Figure 2. Data-driven system application services

4. Case description

4.1. Platform development

This section provides an illustrative example of a radar display map in the ATC system's task execution. A radar map is an event in the ATC system and has long-term high-frequency contact with ACTOs, and is directly related to the intrinsic state of ATCOs, and a reasonable HFs test is a prerequisite for radar map optimisation. Therefore, the above DM framework was applied to the radar display interface as an example to study. **Figure 3** presents a prototype hardware and software system and experimental radar materials. The experimental design considers 12 aircraft on the radar map. One was described as a conflict alert event and displayed flight tag information, which included flight number, speed, and altitude. Attempts were made to optimise the radar display map by using an explorative design study and assisted sketching with the following design setting:

- The radar map from Los Angeles (LAX) International Airport. Sector 38.
- Dotted lines are sector boundaries.
- Solid lines are airways.
- Circles depict airports and navigational radio beacons.
- X's show intersections along the airways.

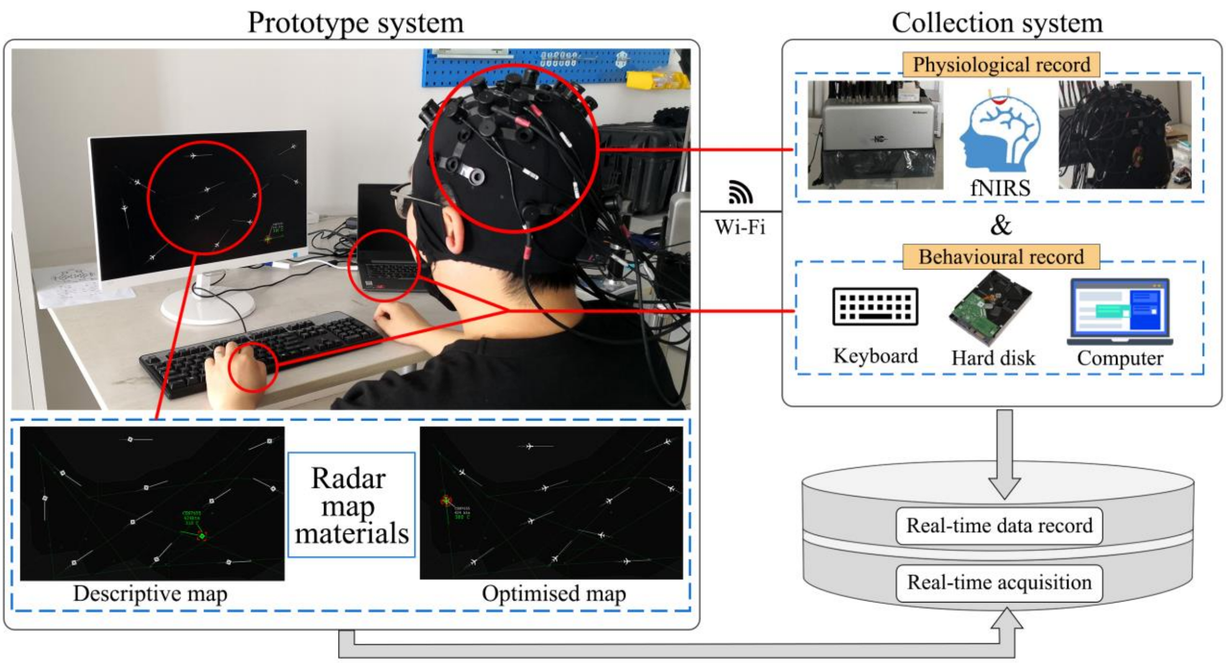

Figure 3. Prototype of the hardware and software system

4.2. Data collection and processing

4.2.1. Data input and collection

4.2.1.1. Subjects

A total of 18 healthy subjects (14males and 4 females, 23-29 years old) with no history of neurological, physical, or psychiatric illness and a certain level of experience of aviation were recruited for this study. The research was conducted at the Industrial Design Research Laboratory of the School of Mechanical Engineering, Shandong University (SDU). All subjects agreed to participate and signed informed consent forms. The experimental methods were approved by the SDU Human Ethics Committee and implemented according to the ethical standards of the 1975 Helsinki Declaration.

4.2.1.2. Experiment procedure

The experiment was divided into three stages: Rest, Task1 (descriptive map), and Task2 (optimised map). Each stage lasted 10 min, with 10 min intervals between stages to ensure the accuracy of the measurement data shown in **Figure 4(A)**. Subjects were required to sit in front of a radar map monitor and be at rest and keep their body as still as possible for 10 min, and the task1-stage and task2-stage were based on the n-back task with n is 2. In the first stimulation, conflict warning aircraft appeared at any position among the 12 aircraft, flying at any altitude. In the subsequent stimulation, conflict warning events occurred at random positions and at random altitudes. Adjusting the flight altitude is the most common way for ATCOs to resolve conflicts and was, therefore, used as a determining factor. The subjects completed cognitive thinking activities by judging whether the $n + 2$ stimulation and the n stimulation conflict warning events were the same in terms of position and flying altitude. The instruction was that if they were all the same, press the "SPACE" key, and if they are different, do nothing. The task1-stage and task2-stage were implemented in E-prime 2.0 psychology software.

4.2.1.3. Physiological data acquisition

The prefrontal cortex of the brain performs advanced neural information processing functions, including memory, judgment, analysis, thinking, and manipulation, and plays a key role in cognitive control [60]. The sensorimotor cortex in the parietal lobe region plays an important role in somatosensory perception, visual body spatial information integration and movement. The occipital lobe is mainly responsible for visual processing. In order to place the probe correctly, spatial positioning information was obtained by using a 3D magnetic locator and spatial positioning acquisition software. The distance between each light source and the detector was 30 mm, which allows optical waves to reach the cortex and keep the signal quality stable and intense. This fNIRS equipment uses a multi-channel commercial near-infrared system (Nirsmart, Danyang Huichuang

Medical Equipment Co. Ltd, China) with a sampling frequency of 10 Hz and set wavelengths of 760 and 850 nm. Based on the international 10/20 system, 22 SD probes were placed on the right prefrontal cortex (RPFC), the left prefrontal cortex (LRFC), the right motor cortex (RMC), the left motor cortex (LMC), the right occipital lobe (ROL) and the left occipital lobe (LOL) to constitute a 22-channel fNIRS system as shown in **Figure 4(B)**.

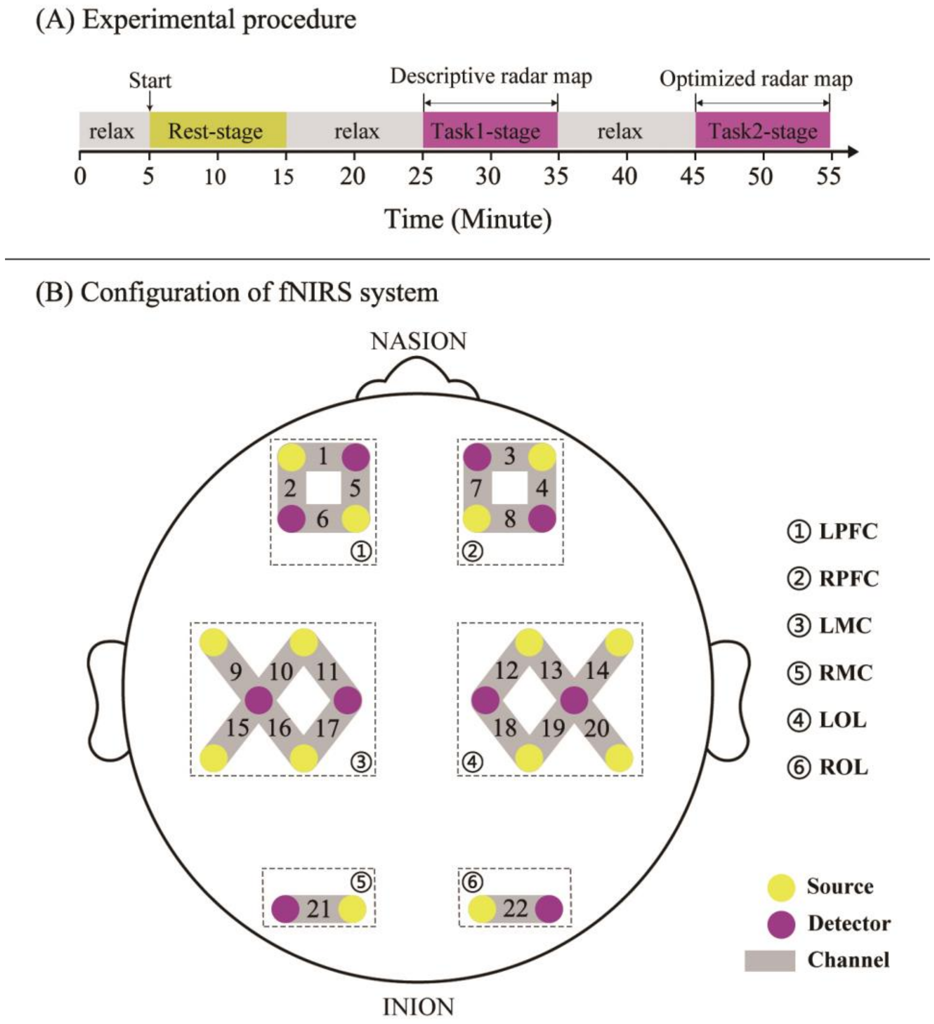

Figure 4. Experiment procedure and the 22-channel fNIRS system

4.2.1.4. Subjective and behaviour record

Subjects were asked to complete a VAS at the end of each stage to discover their subjective psychological feelings. According to the experimental settings, fatigue, comfort, attention, positivity, and stress were selected as the five key indicators. Furthermore, the psychology E-Prime2.0 software was used to record the subjects' behavioural data during operation, including accuracy rate and single reaction time information.

4.2.2. Data analysis and processing

4.2.2.1. Objective data processing

The deletion of irrelevant time intervals in the original data was performed firs; thereafter the data was automatically spliced into a complete continuous time series. After this exclusion process, a series of processing steps was carried out, as shown in **Figure 5**.

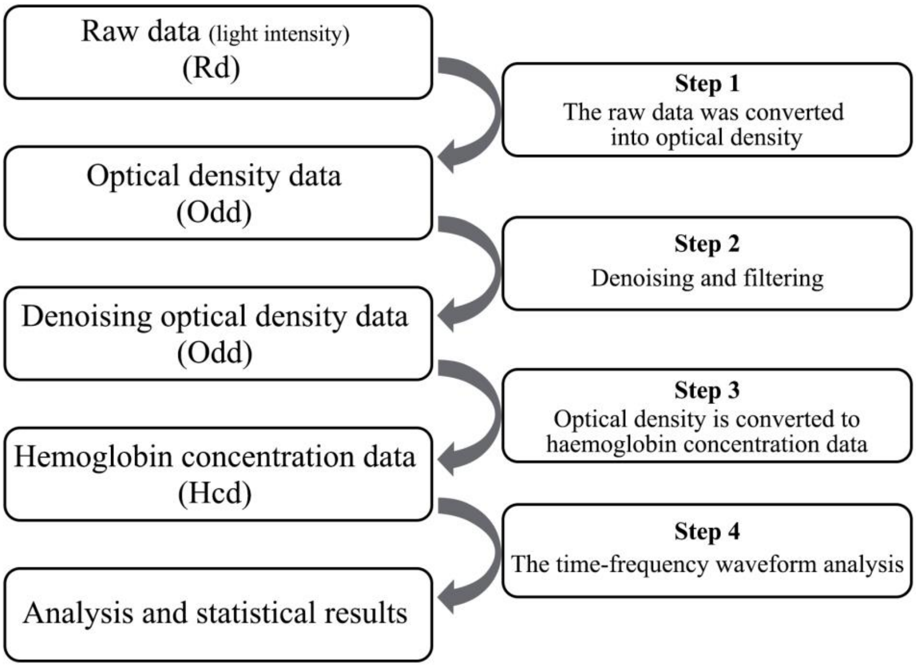

Figure 5. fNIRS data processing analysis flow

First of all, the raw data were converted into optical density. The raw data were light intensity received by the detector (avalanche diode), and changes in light intensity were measured by electrical signals created by emitted light signals [65]. This stage mainly included identifying and removing the artefacts, and finally converting the data the optical density data. Firstly, the sliding average method in Eq. (1) calculates the abnormal signals, such as a noise, caused by the light leakage on the data-time series to improve the SNR. The average value of $2N + 1$ points is used to replace the abnormal points in the original signal. Then, $y(n)$ is the time series after the sliding average, $x(n)$ is the original time series, and the value of N is 2.

$$\mathrm{y(n)} = \frac{1}{2N+1}\sum_{i=1}^{2N+1} x(n-i) \tag{1}$$

Next, the mobile standard deviation was calculated to automatically retrieve the interval of artefacts that may be found in the data. In our experiment, a 0.5-s sliding time window was used to check all the time periods. The detected artefacts made by the movement were modified by spline interpolation and then the processed time series was converted into optical density data, expressed as Eq. (2), where I_1' is the incident light intensity and I_1 represents the emitted light intensity.

$$\Delta \mathrm{Odd} = \log I_1' / I_0 - \log I_1 / I_0 = \log I_1' / I_1 \tag{2}$$

Secondly, denoising and filtering were necessary for data correction. All heartbeat and Mayer waves can be reflected in oxy and deoxy data, but these signals cannot be measured directly because this character and noise are actually detected by optical means, where the direct feedback is the change of Odd data. Hence, filtering Odd data can achieve the same effect and remove the noise caused by physiological signals such as heartbeat [66]. In order to retain the original amplitude of the original signal in the passband to the greatest possible extent, a Butterworth filter was used for processing the optical density data to improve the data quality and ensure the validity and reliability of the data analysis because the interference of high frequency noise and low frequency fluctuation signals were reduced to improve correction and SNR. Further, a 0.01 Hz-0.2 Hz band-pass filter was set to remove low baseline drift and physiological noise due to heartbeats, breathing, cardiac frequencies, and Mayer waves [65]. The expression of the n-order Butterworth filter is as shown in Eq. (3), where fc is the cutoff frequency, fp represents the passband edge frequency, and the value of n is 6:

$$|H(f)|^2 = \frac{1}{1 + \left(\frac{f}{fc}\right)^{2n}} = \frac{1}{1 + \epsilon^2 \left(\frac{f}{fp}\right)^{2n}} \tag{3}$$

Thirdly, optical density was converted to haemoglobin concentration data by using the modified Beer-Lambert law. Haemoglobin concentration data directly reflect changes in the brain nerves during activity. The relative concentrations of oxygenated haemoglobin (HbO_2) and reduced haemoglobin (HbR) detected in the brain tissues were calculated through the modified Beer-Lambert law to obtain the time-series of haemoglobin concentration data. As Eq. (4) shows, DPF is called differential pathlength factors [67] with the value of 6, which accounts for the effective length between source and detector. The value of r is the linear distance between paired probes on the scalp. The delta optical density, $\Delta \mathrm{Odd}^{\lambda_i}$, refers to the change in light absorption. $\varepsilon_{HBO}^{\lambda_i}$, under near-infrared light of wavelength i, is the absorption coefficient of HBO substance, λ represents wave length (1=760 mm, absorption coefficient is $1486.5865\ \left(\frac{cm^{-1}}{mol*L^{-1}}\right)$; 2=850 mm, and the absorption coefficient is $2526.391\ \left(\frac{cm^{-1}}{mol*L^{-1}}\right)$). Moreover, $\varepsilon_{HB}^{\lambda_i}$, under near-infrared light of wavelength i, is the absorption coefficient of HB substance, λ is wave length (1=760mm, absorption coefficient is $3843.707\ \left(\frac{cm^{-1}}{mol*L^{-1}}\right)$; 2=850mm, absorption coefficient is $1798.643\ \left(\frac{cm^{-1}}{mol*L^{-1}}\right)$).

$$\Delta \mathrm{Odd}^{\lambda_i} = \left(\varepsilon_{HBO}^{\lambda_i}\Delta C_{HBO} + \varepsilon_{HB}^{\lambda_i}\Delta C_{Hb}\right)\cdot r \cdot DPF \tag{4}$$

Fourth, time-frequency waveform analysis was performed. The data were further analysed (e.g., cortical activation, brain functional connectivity) to visualise the implications of the results. The transformation from the original optical data to the blood oxygen concentration was completed by applying the above algorithm, and the time series of each channel was obtained, representing the functional activity attributes and cooperation level of corresponding brain regions. The connectivity attributes between cortical regions were measured by the correlation between the time series data. The Pearson correlation analysis method was used to calculate the correlation by substituting the relevant values in Eq. (5), where $x_i(k)$ and $x_j(k)$ are the k-th data value of the i-th and j-th channel time series; K is the total number of sequence values; x_i and x_j are the average values of the channel sequence.

$$r_{ij} = \frac{\sum_{k=1}^{k}[x_i(k) - \overline{x_i}][x_j(k) - \overline{x_j}]}{\sqrt{\sum_{k=1}^{k}[x_i(k) - \overline{x_i}]^2 \sum_{k=1}^{k}[x_j(k) - \overline{x_j}]^2}} \tag{5}$$

To judge the difference of cooperation among the three stages (rest, task-1 and task-2 stages) of brain regions to provide clear guidance for the DM process, the significant differences among three stages were further analysed. Firstly, the strength of functional connectivity between brain regions in the three stages was calculated to evaluate whether the data exhibited a normal distribution, without outliers and spherical assumption. Then the functional connectivity in three stages was analysed by one-way repeated ANOVA measurement. Three stages were internal variables, and functional connectivity was the observed influencing factor. Finally, the functional connectivity of each stage was further compared in pairs. $P < 0.05$ showed that there was a significant difference in functional connectivity.

4.2.2.2. Subjective data processing

The subjective and behavioural data were stored and summarised. The Shapiro–Wilk test was used to test the normal distribution of the data, and the box plot of each group of data was used to determine the presence of abnormal values. A paired-sample t-test was used for the data that met the normal distribution and the Wilcoxon signed-rank test was used for non-compliance. The comparison of the three sets of data needed to simultaneously conform to the normal distribution, without outliers and spherical assumptions, and then descriptive statistics and mean analysis were conducted. One-way repeated measurement ANOVA was used to detect significant differences between the subjective scales in three different stages, so as to further explain the difference between the subjective data in each two stages. $p < 0.05$ was statistically significant.

4.3. Application and results

4.3.1. Physiological results

The results are shown in **Figure 6.** The intensity of the functional connectivity between LPFC and RPFC regions of the brain in the three stages was observed to be the highest of each stage. Their correlation coefficients were, in the rest-stage r=0.8222, and in the task 1-stage r=0.7987 and in the task-2 stage r=0.8688. Further, the correlation between RMC and ROL in the rest-stage was the lowest, r=0.2017. In the task1-stage, the functional correlation between LOL and ROL was the lowest, r=0.0915. Similarly, the lowest degree of correlation between LOL and ROL appeared in the task2-stage, r=0.1659.

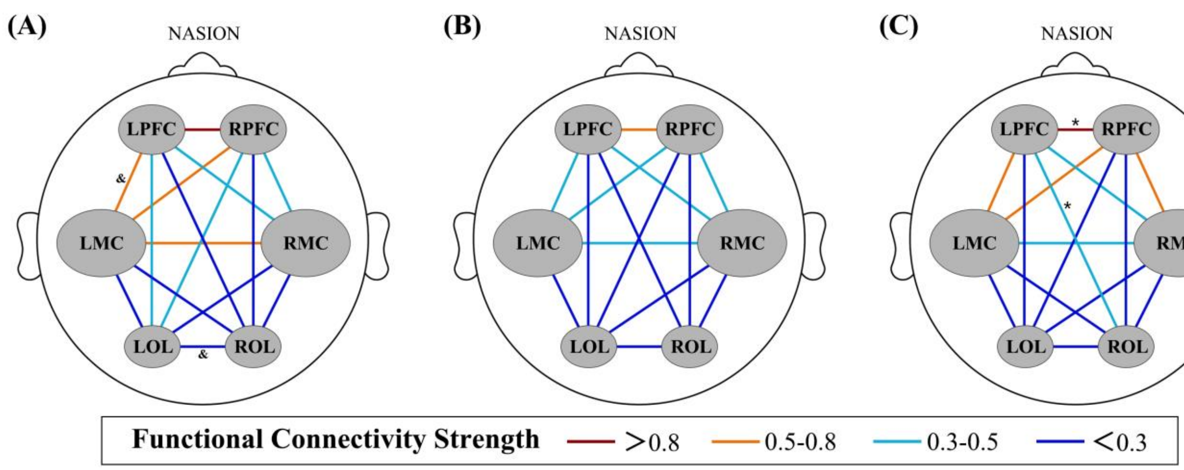

Figure 6. The strength of functional connectivity between brain regions in three stages. A. Rest-

stage correlation; B. Task1-stage correlation; C. Task2-stage correlation. Significant differences in functional connectivity after ANOVA are marked with $*p < 0.05$ between the task1-stage and task2-stage, and $^{\&}p < 0.05$ between the rest-stage and task-stage.

The functional connectivity strengths of LPFC and RPFC ($F = 5.152, p = 0.011$), LPFC and LMC ($F = 4.307, p = 0.022$), LPFC and ROL ($F = 5.914, p = 0.006$), LOL and ROL ($F = 4.396, p = 0.02$) in rest-stage, task1-stage and task2-stage were statistically significant. Compared with task1-stage, the functional connectivity strength of LPFC and LMC in the rest-stage was significantly improved by 0.096 ($p = 0.023$, corrected). Compared with the task1-stage, the connectivity strength of LOL and ROL in the rest-stage significantly increased by 0.169 ($p = 0.01$, corrected). The LPFC and RPFC functional connectivity in the task2-stage was significantly improved by 0.070 ($p = 0.012$ correction). Meanwhile, the functional connectivity between LPFC and ROL in the task2-stage increased significantly by 0.181 ($p = 0.014$ corrected). It is worth noting that there was no significant difference between the rest-stage and task2-stage. The ANOVA analysis of the functional connectivity of brain regions in the three stages showed that the functional connectivity strengths of certain brain regions in the task2-stage and rest-stage were improved compared with the task1-stage.

4.3.2. Subjective results

The results of the subjective VAS scale are shown in **Figure 7**. The rest-stage, task1-stage, and task2-stage in Fatigue ($F = 28.620, P < 0.001$), Attention ($F = 7.101, p = 0.003$), Training Positive ($F = 8.269, P = 0.001$), Pressure ($F = 22.481, p < 0.001$) demonstrated statistical significance. Among these, the fatigue aspect of the rest-stage was significantly reduced by 4.667 ($p < 0.001$) as compared to the task1-stage, and 4.222 ($p < 0.001$) was a significant reduction as compared to the task2-stage. The attention level at the rest-stage was significantly lower than at the task1-stage by 2.611 ($p = 0.042$), and was significantly lower than in the task2-stage by 2.722 ($p = 0.021$). The stress perception in the rest-stage was significantly lower than in the task1-stage by 4.611 ($p < 0.001$), which was further significantly lower than the task2-stage by 2.944 ($p < 0.001$). However, with the task training positive, only the task2-stage was significantly improved by 3.167 ($p = 0.012$) compared to the rest-stage.

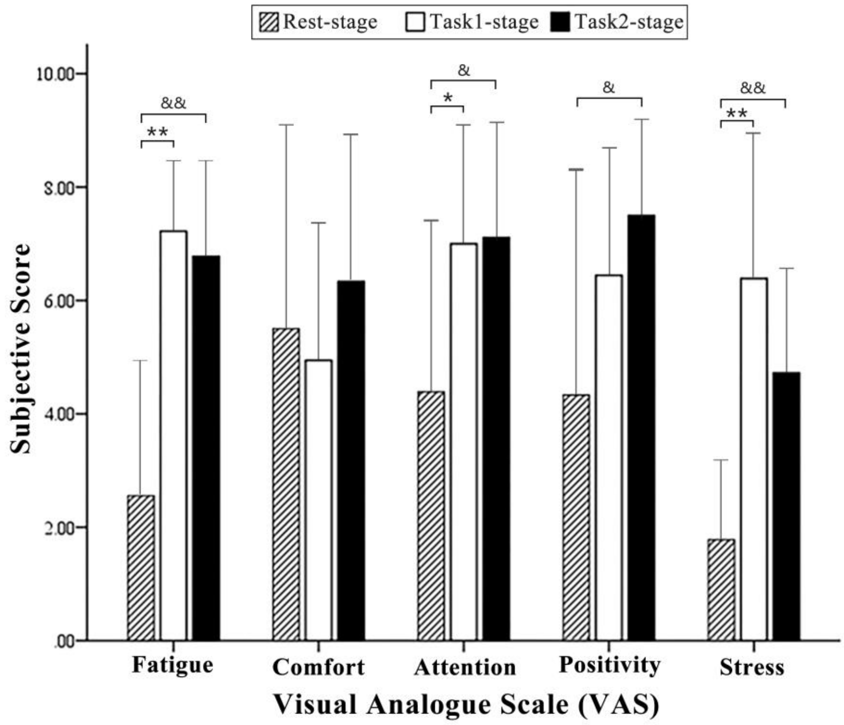

Figure 7. Results of the VAS scale at each stage. Significant differences in subjective score are marked with $*p < 0.05$ or $** p < 0.01$ between the rest-stage and task1-stage, and $^{\&} p < 0.05$ or $^{\&\&} p < 0.01$ between the rest-stage and task2-stage.

In this research, E-Prime software was used to record the subjects' level of accuracy and reaction time during operations as shown in **Figure 8**. The total number of errors in the task1-stage was 6.8 (3.1 in the first half and 3.8 in the second half), while the total number of errors in the task2-stage was 5 (2.4 in the first half and 2.5 in the second half). Meanwhile, in the reaction time aspect, the average reaction time in the task1-stage was 980 ms, 959 ms in the first half, and 1004ms in the second half. The average response time in the task2-stage was 935 ms, 941 ms for the first half and 929 ms for the second half. Interestingly, the accuracy rate and response time between the task1-stage and task2-stage were not statistically significant. However, accuracy and response time were both superior in the task2-stage than in the task1-stage. Especially the response time in the second half of the task2-stage was reduced though the accuracy remained high.

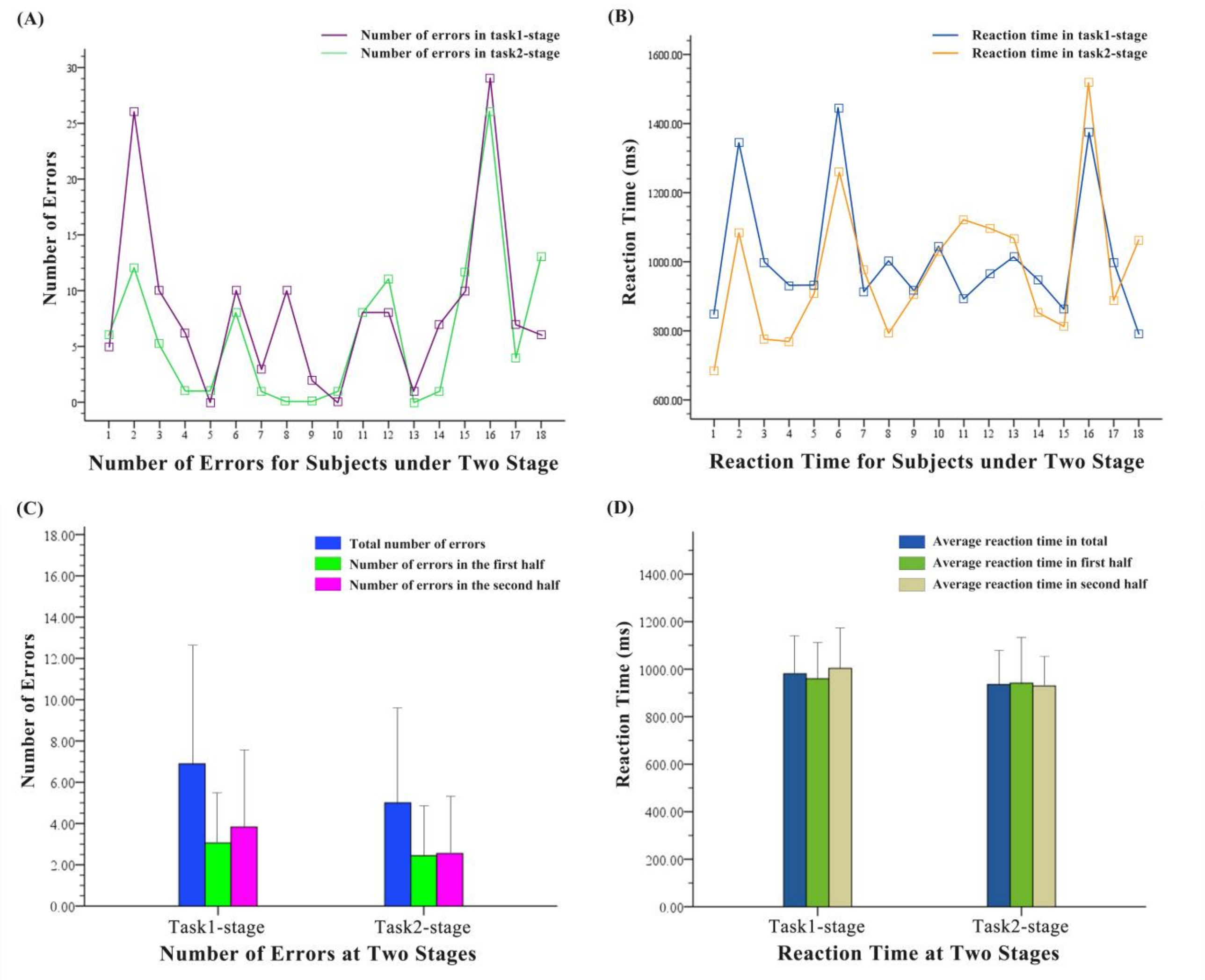

Figure 8. Analysis of the result of behaviour data in the task1-stage and task2-stage. (A) The number of errors committed by each subject in the two stages. (B) Average reaction time for each subject in the two stages. (C) The number of errors in total, first half, and the second half of the task1-stage and task2-stage. (D) The total reaction time of all the subjects, first half and second half of the task1-stage and task2-stage.

4.3.3. Interpretation of the results

4.3.3.1. Physiological meaning

The brain signals detected by fNIRS mainly stem from the changes in brain neural activity while performing the task. Based on neurovascular coupling theory, functional connectivity is a significant indicator of brain activity, which can directly analyse the cooperative level in the brain's complex area. The stronger the functional connectivity between brain regions, the stronger the cooperation between brain regions, which helps subjects reach higher performance levels and maintain higher attention levels. Therefore, the functional connectivity strength is an intuitive expression of the degree of a user's cognitive state which might lead to the occurrence of human error.

4.3.3.2. Relationship between results and application

Normalised results of subjective, behavioural and physiological data are considered in the interpretation of the experiment. The execution of cognitive control is mainly carried out in the prefrontal lobes. LPFC and RPFC functional connectivity strength in the task2-stage was the highest, even higher than in the rest-stage, and it is significantly lower in the task1-stage than in the task2-stage, indicating that an optimised radar map with HFs is better than a descriptive radar map and more suitable for users' cognitive mental fatigue state. Although there was no significant difference in the behavioural data, it can be judged intuitively that the task2-stage is better than the task1-stage in regard to time and accuracy. Meanwhile, regarding the subjective aspect, it also emphasises again that the task2-stage's training positivity is superior to the other two stages. In this connection, synchronisation has occurred between subjective and objective data.

These results can be applied together to generate service options, such as cognitive fatigue threshold, comfort prediction, and internal state monitoring. The ATCOs' cognitive state was evaluated to determine whether the intervention behaviour of the system was turned on or not, and the operational behaviour beneficial to the ATCOs' current state was formed. In this case study, for the adaptive DM process, the functional connectivity level for both the task1-stage and task2-stage was not significantly lower than that of the rest-stage, which means that ATCOs' cognition and ability enable them to deal with the potential conflictions by adjusting an aircraft's angle, altitude, or other elements. If the functional connectivity strength in an event is significantly lower than that of the rest-stage, which indicates that the event has caused ATCOs fatigue, which will probably lead to operation errors, the system should change automatic level to take over ATCOs' behaviour based on the signals received in real time, for instance, strengthening the automatic control level, creating stimulating signals to assist users, or providing the alternative solutions for ATCOs, or even taking over the operation, and so on until the user's cognition recovers. In addition, for human-machine fusion, based on the subjective and objective data, it also suggested that this type of visual aid that the optimised radar map provides a design reference, which can effectively avoid human error and provide a direction for future design and development of ATC system elements.

5. Discussion

Detecting cognitive fatigue is a key problem in developing adaptive systems and has been proven to improve human-computer interaction [68]. The research conducted by Lyu et al. [47] focuses on the previous experience and determined the common human factor influence ranking through the HFACS-BN model, so as to guide the optimisation of the system. By contrast, this research can effectively monitor the user and system behaviour data in real time through the proposed data-driven framework. Then the data are processed by the framework data analysis section (characteristics process). And finally, according to the characteristics (range and threshold, extreme value, and significance compared to the resting state) of the data, the adaptive adjusting behaviour (the degree of automation, the replacement of two-dimensional or three-dimensional design presentation elements) of the system or keeping the original state is decided in a multi-dimensional way. This step is similar to a mock recogniser (characteristics recognition) that determines the user's level of cognitive status and then provides a basis for the system to be adaptive.

The complex cognitive information required by the human-machine interaction interface may come from two sources, namely the required operations and the information prompts. Both sources depend on how the user interacts with the target task under the information support structure (such as visual assistance, interactive media). Therefore, the design of the radar map considers the similarities between the elements and the observed transformation operations of the elements. The fNIRS considers the brain regions, namely prefrontal lobe, parietal lobe, and occipital lobe through 22 channels. The prefrontal lobe is related to the DM process, working memory and attention. Therefore, the more complex the cognitive information, the higher the HbO_2 in the prefrontal lobe brain region. In this case, the functional connectivity values of significant interactions were averaged for 15 directed interregional connection types between all possible pairs of 22 channels in each subject, and thereby, the mutual interactions among the six regions were analysed.

The prefrontal lobe maintains high connectivity among the three stages, but of the two task stages, the task1-stage is weakened at the functions' connection, which reflects the reduced transmission efficiency of this area. The parietal lobe is related to procedural memory and vision. The longer the memory consolidation, the stronger the visual stimulation, and the higher the HbO_2 level in the parietal lobe. In the task2-stage, the functional connectivity between the left and right parietal regions and LPFC and RPFC were higher than for the task1-stage, indicating that appropriate visual auxiliary elements, such as object and important data indicator enhancement prompts and object visualisation, are conducive to the positive linkage effect of vision, memory and cognitive DM. Design elements research studied by Luciani et al. [43] and Van Paassen et al. [44] demonstrate that the visualisation auxiliary can help ATCOs operate the ATC system better, which is similar to our research. The rest-stage has a positive significant difference compared to the task1-stage, the task2-stage has a positive significant difference compared to the task1-stage, and there was no significant difference between the rest-stage and task2-stage, which may indicate that the optimised map task is closer to the resting state, and a descriptive map makes subjects fatigued. Meanwhile, according to the subjective results, it was found that the task2-stage's training positivity is significantly higher than for the rest-stage, while the results of the task1-stage and rest-stage have no significant difference. From the behaviour analysis, the average number of errors and the average response time of the task2-stage are lower than for the task1-stage, indicating that the optimal design of visual AIDS is expected to contribute to ATCOs' training, which can effectively avoid human error and provide a direction for future design and development in the ATC field.

From the aforementioned work on the memory task by ATCOs, one can see that good results have been achieved in brain functional connectivity and subjective analysis, such as maintaining normal function connectivity and improved accuracy and reaction time. Dehais et al. [69] also indicated undesirable neurocognitive states, such as mind wandering, while inattentional phenomena can negatively affect ATCOs' operation (increase human error rate and reaction time). Simultaneously, it also establishes that the DM framework can usefully apply HFs to the ATC system to avoid unilateral judgment errors, without causing a significant difference in behaviour. This can avoid the wastage of time and money, and achieve the timely adjustment of the system in response to behavioural changes and system performance decline. Meanwhile, fNIRS is sensitive to different levels of cognitive fatigue, which is consistent with the study by Durantin et al. [68].

6. Managerial implications

This framework will further aid understanding of the performance of humans and machines for intelligent adjusting of the system's DM behaviour in relation to the external and internal working conditions and the skills, tasks and cognitive abilities of specific personnel, through intuitive data and good synchronisation. The results can support the combination with ATC system applications. The system behaviour can be adjusted accordingly via the data-driven approach. The possible applications mainly include: real-time online feedback that eases the capturing of the state of ATCOs to realise human-centred system adjustment, safety warning reminders according to the critical point of information implied by the data and level of automation in the human-machine interface. Also, it serves as a data-driven model that provides objective data to empirically prove the advantages and disadvantages of applications of HFs and further supports the subsequent design optimisation. Hence, these new data results provide insights into ATCOs interactions with the whole system interface and with a single field of interest and indicates the potentials for IA of ATC.

Data-driven adaptive DM supports and regulates system parameters, including adaptive automation level, workload scheduling, ergonomics interface and interaction. According to the ATCOs' real-time physiological state – mainly cognitive state – the behaviour of the system is adjusted automatically to adapt to the ATCOs. When ATCOs change from slight fatigue to high cognitive fatigue, that is, the brain functional connectivity falls below the normal range, the system will automatically determine that the ATCOs' cognitive fatigue is at danger level according to the findings of the cognitive fatigue simulation recogniser, and then improve the automatic operation level (from low to high) and add wake-up signals (the preferred warning graphics and tone) (**Figure 9**). For instance, when there is a possibility of aircraft conflict, the system will pop up optimal operation – adjust the plane's altitude (but not necessarily the most appropriate solution) – for ATCOs' selection to reduce their mental pressure. Meanwhile, triggered warning signals based on design elements will appear to awaken ATCOs' mind, which relieves ATCOs' workload, helps to restore cognition and also is able to guarantee the safety of the aviation system. When the system detects that ATCOs are operating at a reasonable level, the system's responsible behaviour will disappear and the ATCOs will manually adjust the best solution (more factors, such as weather conditions, can be considered comprehensively).

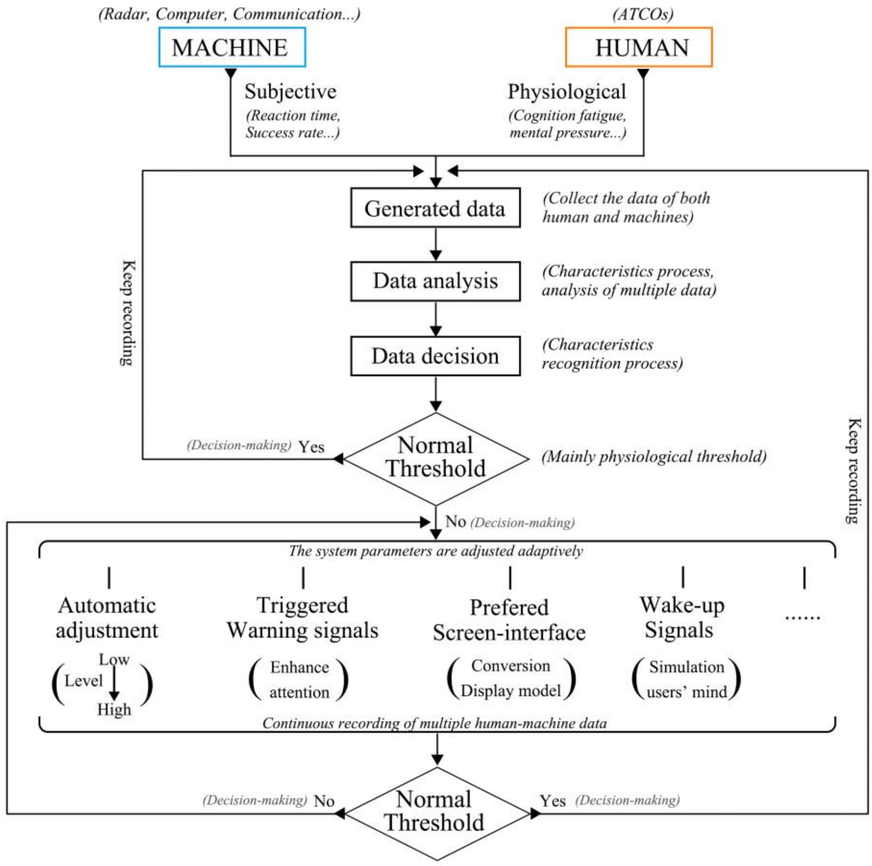

Figure 9. Adaptive DM mechanism based on the data-driven framework

The real-time online feedback system can also be incorporated into ATC operation to distinguish state changes when ATCOs participate in different human factor tasks to extract and identify new opportunities for its application in future HFs design applications. By interpreting the resource allocation between brain regions, such as whether multiple brain regions can be mobilised, or which brain regions are more effective, we can speculate about the internal effects of different factors on ATCOs. The above can serve as a basis for adaptive decisions of the system (preferred elements design, warning signal, and so forth). The priority of the design elements concerning HFs in regard to system aspects will be formed, which can provide guidance for the future system design and transformation, as well as being a way to show the two-dimensional and three-dimensional elements. Then subjective data can be combined to identify different human behaviour factors, patterns, and plans, and find the optimal design elements which need improvement, to support the design and development of different modes of human-machine interfaces.

The proposed method can also be extended to situation awareness. As a method should be provided to observe the individual factors influencing ATCOs, which is convenient for identifying the critical points of ATCOs including fatigue, pressure and workload and also to identify the most common factor relationships that negatively or positively affect ATCOs' performance, to propose several sets of core factors, provide hypotheses for further research, and combine with ATCOs' safety performance models or training programmes to establish effective human performance management.

7. Conclusion

The field of engineering, especially automation and control engineering, is further exploring adaptive DM methods to reduce the occurrence of human error and the risk index of engineering. HFs play an important role in DM, especially in the ATM field where ATCOs are at the centre of DM. At present, most of the research is limited to the level of automation of operation systems. However, obtaining feedback on ATCOs' performance is difficult, which makes it impossible to scientifically monitor human behaviour in real time. In this context, this paper proposes a subjective and objective data-driven adaptive DM method based on fNIRS, which takes ATCOs' internal state as the dominant supporting factor in decision behaviour. The main contributions are summarised as follows:

- A novel framework and approach for adaptive DM based on fNIRS from the user's perspective is proposed, which captures the internal status and defects in the performance of users to achieve human-centred automatic adjustment.
- A novel data collection and processing method is proposed, which can directly reflect and evaluate the user and system status. In addition to considering the user experience and machine behaviour data, the objective physiological data of the user in the operation process is also fully considered.
- Data-driven methodology combining subjective and objective data is proposed to detect the impact of system factors on the user, ensure the accuracy and validity of data, and understand the best facilitation for maximising human performance in the ATC environment.
- The application of HFs in the system was evaluated to support element design optimisation so that the performance of HFs in design and manufacturing lays the foundation for the realisation of the IA of the system.

To make the research framework more specific, the feasibility of DM proposed in this paper was verified through the radar case study, which can play a certain role in promoting the application of human-centred subjective and objective data-driven applications in the future ATC environment in adaptive decision research.

This paper is limited to research of human-machine interfaces. The whole ATC system also has tools, procedures, roles and communication flows, which have not been covered in this study and need to be considered in the future. Also, the follow-up study should be more than an hour-long task designed to mimic the real work situation. Future work should focus on applying the proposed methodology to multiple complex environments involving more users to explore more data-driven system application services, so as to promote the development of system IA and DM.

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